Fundación de Estudios de Economía Aplicada

Assesing the economic value of nearest-neighbour exchange-rate forecasts*

by

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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 and the traditional (linear) ARIMA(1,1,0) predictors, transforming their forecasts into a technical trading rule, whose profitability (considering both interest rates and transaction costs) is evaluated against a simple buy-and-hold strategy. Our results suggest that in most of the cases a trading rule based on a nonlinear predictor outperform that based on an ARIMA predictor, both in terms of returns and in terms of the ideal profit and the Sharpe ratio profitability indicators. With only one exception, the net returns from technical trading rule dominate those from a buy-and-hold strategy .

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"Investment based on genuine long-term expectation is so difficult...as to be scarcely practicable. He who attempts it must surely run greater risk than he who tries to guess better than the crow how the crow will behave".
Keynes (1936, 156)

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. Finally, note that the NN approach to forecasting is related to techniques of charting (technical analysis) applied in financial markets to produce short-term forecasts [see, e. g., Elms (1994)].

Meese and Rose (1990), Diebold and Nason (1990) and Mizrach (1992) applied NN methods to analyse exchange-rate nonlinear predictability. These papers found that their predictions are not better than forecasts generated by a simple random walk model. 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.

Using NN methods, Fernández-Rodríguez and Sosvilla-Rivero (1998) 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.* (1998) 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.

The purpose of this paper is to assess the economic significance of the predictability of EMS exchange rates. To that end, the predictions are transformed into a simple trading strategy, whose profitability is evaluated against a simple buy-and-hold strategy based on the random walk model and its distance from the ideal net profit[1]. When evaluating trading performance, we will consider both interest rates and transaction costs.

We have applied this investment strategy 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 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

[1] Gençay (1998) follows a similar approach to investigate the profitability of using artificial neural networks in security markets.

of the sample. In the case of the Spanish peseta, the Pound sterling and the Portuguese escudo, the recursive forecasting process starts the joining date (9 June 1989, 8 October 1990 and 9 April 1992, respectively).

The paper is organised as follows. Section 2 presents the NN predictors and the empirical results are reported in Section 3. Some concluding remarks are provided in Section 4.

2. NN and SNN predictors

Let x_t (t=1,...,T) be a finite time series. In order to identify geometric patterns in the time series, segment with similar dynamic behaviour are carefully chosen and used afterward to formulate a forecast of the next term in the series (i. e., x_{T+1}). This forecast is computed as some adequate average of the time series values that immediately follow the identified segments. The segments have equal length, and are considered as points in a real vector space whose dimension is called an embedding dimension for the series. Therefore, we consider vectors $x_t^{m,\tau}$ of m observations sampled from the original time series at intervals of $\tau \in \mathbb{N}$ periods:

$$x_t^{m,\tau} = (x_t, x_{t-\tau}, \ldots, x_{t-(m-1)\tau}),\ t=1+\tau(m-1),\ldots,T \tag{1}$$

with m referred to as the embedding dimension and τ called the delay parameter. These m-dimensional vectors are often called m-histories, while the m-dimensional space $\mathbb{R}^m$ is referred to as the phase space of time series. In order to simplify, we shall only consider the case of $\tau=1$ and we shall write $x_t^{m,1} = x_t^m$.

As a second step, we consider the k m-histories

$$x_{i_1}^m, x_{i_2}^m, x_{i_3}^m, \ldots, x_{i_k}^m, \tag{2}$$

most similar to the last available vector

$$x_T^m = (x_T, x_{T-1}, x_{T-2}, \ldots, x_{T-(m-1)}), \tag{3}$$

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

The proximity of two m-histories in the phase space $\mathbb{R}^m$ allows us to talk of "nearest neighbours" in the dynamic behaviour of two segments in the time series x_t. Traditionally, to establish NNs to x_T^m, one looks for the closest k vectors [expression (2)] in the phase space $\mathbb{R}^m$, in the sense that they maximise the function:

$$\rho(x_i^m, x_T^m) \tag{4}$$

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

Finally, once the nearest neighbours to x_T^m have been established, we consider predictors of the future evolution of x_T^m. Let $\hat{x}_{T+1}$ be a predictor of x_{T+1}. This can be obtained using some extrapolation of the observations

$$x_{i_1+1},\ x_{i_2+1},\ \dots\ ,\ x_{i_k+1} \tag{5}$$

subsequent to the k nearest neighbours m-histories chosen, that is to say:

$$\hat{x}_{T+1} = F(x_{i_1+1},\ x_{i_2+1} \dots,\ x_{i_k+1})$$

For every T, we considering the following local regression model:

$$\hat{x}_{T+1} = \hat{a}_0 x_T + \hat{a}_1 x_{T-1} + \dots + \hat{a}_{m-1} x_{T-(m-1)} + \hat{a}_m \tag{6}$$

whose coefficients have been fitted by 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,..., k). Therefore, the $\hat{a}_i$ are the values of a_i that minimise

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

Alternativelly, and following by Fernández-Rodríguez, Sosvilla-Rivero and Andrada-Félix (1998), 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,...,T) and y_t (t=1,...,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, we embed each of these series in the vectorial space $\mathbb{R}^{2m}$, paying attention to the following vector:

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

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

Hence, 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:

$$\rho(x_i^m, x_T^m) + \rho(y_i^m, y_T^m), \quad i=m,m+1,\ldots,T. \tag{7}$$

In this way, we obtain a set of k simultaneous m-histories in both series:

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

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

$$\ldots$$

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

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:

$$\hat{x}_{T+1} = \hat{a}_0 x_T + \hat{a}_1 x_{T-1} + \ldots + \hat{a}_{m-1} x_{T-(m-1)} + \hat{a}_m \tag{8a}$$

$$\hat{y}_{T+1} = \hat{b}_0 y_T + \hat{b}_1 y_{T-1} + \ldots + \hat{b}_{m-1} y_{T-(m-1)} + \hat{b}_m \tag{8b}$$

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

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

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 (6) 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, members 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.

3. Empirical results

Predictability of financial prices in itself does not guarantee that an investor can earn profits from a trading strategy based on such forecasts. As was suggested by Leitch and Tanner (1991), standard measures of predictive performance like the root-mean-squared error may not be closely related to economic profits.Therefore, we consider a simple technical trading strategy in which positive returns are executed as long positions and negative returns are executed as short positions. The estimated total return of such strategy is given by:

$$R^{t}_{T} = \sum^{n}_{i=1} z_t \;\; r_t \tag{9}$$

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:

$$r_t = ln\ (E_{t+1}) - ln(E_t) - ln\ (1+i_t) + ln\ (1+i^*_t) \tag{10}$$

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

On the other hand, with one-way proportional transaction cost c, the net return of the technical trading strategy is given by:

$$R^{n}_{T} = \sum^{n}_{i=1} z_t\, r_t - \ nrt\ \{ln(1\text{-}c) - ln(1+c)\} \tag{11}$$

where nrt is the number of round-trip trades.

To compare the performance of this simple technical trading strategy, the net returns on a simple buy-and-hold strategy:

$$R^{n}_{B} = ln\ (E_{t+\eta}) - ln(E_t) \ - \{ln(1\text{-}c) - ln(1+c)\} \tag{12}$$

is used as the benchmark, where η indicates the holding period.

The estimated total and net returns are calculated by:

$$R^{t}_{T} = \sum^{n+\eta+1}_{i=n+1} \hat{z}_t \, r_t \tag{13}$$

and

$$R^{n}_{T} = \sum^{n}_{i=1} \hat{z}_t - \; nrt \; \{ln(1\text{-}c) - ln(1+c)\} \tag{14}$$

where $\hat{z}_t$ is the estimated recommended position for the tth observation. The estimation of $\hat{z}_{tt}$ is carried out by the three different forecasting methods examined in Fernández-Rodríguez *et al.* (1998): NN predictors, SNN predictors and ARIMA(1,1,0) predictors. Regarding the transaction costs, following Levich and Thomas (1995) and Osler and Chang (1995), we consider a one-way cost of 0.025%.

Tables 1 and 2 report the estimated total and net return, respectively. As can be seen in Table 1, only in 3 of the 9 cases considered (ESC, PTA and UKL) the trading rule based on a linear (ARIMA) predictor outperform that based on a nonlinear (NN or SNN) predictor. From Table 1, we can also see that in 4 out of 9 cases (BFR, DKR, HFL and LIT), the total returns from when using the SNN predictors are the highest, while for the cases of the FF and the IRL, it is the trading system based on the NN predictor the rule that yields the highest total returns. On the other hand, it can be argued that transaction costs may erode the profits from trading in the financial markets based on recursive forecasts. In this sense, compared to the natural benchmark of a buy-and-hold strategy in the market portfolio (which is a relatively passive investment strategy and hence incurs low transaction costs), an investment strategy based on recursive forecasts is likely to incurr considerably higher transaction costs and may not be as profitable as the buy-and-old strategy when transaction costs are appropriately taken into account. Nevertheless, and as can be seen from Table 2, the technical trading returns dominate the buy-and-hold net return in all the cases,except for the IRL. In 5 of such cases (BFR, DKR, FF, HFL and LIT), the trading system based on the SNN predictor give the highest return, whereas in the case of the FF the highest return are obtained when using the NN predictors. Finally, in the cases of the ESC, PTA and UKL, the highest return are associated with the ARIMA predictors.

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

$$R_I = \frac{\sum_{t=n+1}^{n+\eta+1} \hat{z}_t r_t}{\sum_{t=n+1}^{n+\eta+1} |r_t|} \tag{15}$$

According to equation (15), R_I= 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_I= -1. An R_I= 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 mean return of the trading strategy divided by its standard deviation:

$$S_R = \frac{\mu_{\hat{R}_T}}{\sigma_{\hat{R}_T}} \tag{16}$$

According to equation (16), the higher the Sharpe ratio, the higher the return and the lower the volatility. The results for these additional profitability measures are reported in Tables 3 and 4.

As can be seen in Table 3, the ideal profit measure is always greater than zero, except for the UKL, where the trading rules based on the nonlinear predictors render negative values. In all the remainder cases (except the Iberian currencies), using the nonlinear predictors to generate sell/buy signals produce the highest values of this profitability measure. As for the Sharpe ratio, a similar pattern emerges from Table 4: the use of nonlinear predictors as trading rules yields the highest Sharpe ratios in the 6 out of the 9 cases, while for the ESC, PTA and UKL, the highest values are obtained from the trading strategy based on the ARIMA predictors.

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 realignmented), 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 ± 15%).

The results (not shown here, but are available from the authors upon request) indicate is a significantly improve in the profitability of the trading rules based on the nonlinear predictors for those subperiods and currencies where some nonlinear forecatability was found in Fernandez-Rodríguez and Sosvilla-Rivero (1998). We read this aditional evidence to say that there seems to be a close relationship between the forecast performance and the credibility of the exchange-rate commitments. Indeed, as shown in Krugman (1991), if a target zone arrangement as the ERM is credible, there is a nonlinear relationship between the exchange rate and the fundamentals that improves exchange-rate stability.

4. 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) and the traditional (linear) ARIMA(1,1,0) predictors to nine currencies participating in the ERM of the EMS, using daily data of exchange rates vis-à-vis the Deustche 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 (taking into account both interest rates and transaction costs) has been evaluated against a simple buy-and-hold strategy based on the random walk model.

The main results are as follows. Firstly, when profitability was measured using total return, in 6 of the 9 cases considered the trading rule based on a nonlinear (NN or SNN) predictor outperform that based on a linear (ARIMA) predictor.

Secondly, when estimating net return, the trading system based on the nonlinear predictors give the highest returns in 6 out of the 9 cases considered, whereas in 2 cases the highest return are associated with the ARIMA predictors. Only in one case, the buy-and-hold stratregy dominates the technical trading returns.

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 6 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 foreword 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., LeBaron (1996) and Neely and Weller (1997)].

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TABLE 1: Total return: (1)

	NN predictor	SNN predictor	ARIMA(1,1,0) predictor
BFR (2) (5)	0.4711	0.4966	0.1094
DKR (2) (5)	1.4720	1.5560	1.3285
ESC (3) (6)	0.0841	0.2492	0.3062
FF (2) (5)	1.3722	1.3548	0.9525
HFL (2) (5)	0.8467	0.8866	0.6788
IRL (4) (5)	0.4175	0.2695	0.3109
LIT (3) (5)	1.4973	1.8315	1.5696
PTA (3) (7)	0.1618	0.2318	0.4036
UKL (4) (8)	-0.2521	-0.0325	0.2249

Notes: (1) Returns generated by each forecasting method over the forecast sample, before transaction fees are taken into account [see equation (1') 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 2: Net return:

	NN predictor (1)	SNN predictor (1)	ARIMA(1,1, 0) predictor (1)	Buy-and-hold (2)
BFR (3) (6)	0.0156	0.0411	-0.3461	-0.0002
DKR (3) (6)	1.1205	1.2045	0.9770	0.0029
ESC (4) (7)	-0.0714	0.0937	0.1507	-0.0056
FF (3) (6)	1.0240	1.0065	0.6043	0.0028
HFL (3) (6)	0.4702	0.5101	0.3023	-0.0022
IRL (5) (6)	-0.0272	-0.1752	-0.1339	0.0039
LIT (4) (6)	1.1558	1.4900	0.9939	0.0028
PTA (4) (8)	-0.0737	-0.0037	0.1681	-0.0156
UKL (5) (9)	-0.5006	-0.2828	-0.0235	-0.0284

Notes:
(1) Returns generated by each forecasting method over the forecast sample, after transaction fees are taken into account [see equation (2') in the text].
(2) Returns generated using equation (3) in the text, where transaction fees are taken into account
(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: Ideal profit ratio (1)

	NN predictor	SNN predictor	ARIMA(1,1,0) predictor
BFR (2) (5)	0.2713	0.2861	0.0630
DKR (2) (5)	0.3763	0.3978	0.3396
ESC (3) (6)	0.0561	0.1537	0.1889
FF (2) (5)	0.4199	0.4145	0.2915
HFL (2) (5)	0.5909	0.6188	0.4737
IRL (4) (5)	0.1541	0.0995	0.1147
LIT (3) (5)	0.2600	0.3181	0.2726
PTA (3) (7)	0.0574	0.0822	0.1432
UKL (4) (8)	-0.0814	-0.0111	0.0727

Notes:

(1) The ideal profit measures the returns of the trading system against a perfect predictor [see equation (4) 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 4: Sharpe ratio (1)

	NN predictor	SNN predictor	ARIMA(1,1,0) predictor
BFR (2) (5)	0.1652	0.1745	0.0379
DKR (2) (5)	0.3129	0.3327	0.2799
ESC (3) (6)	0.0320	0.0953	0.1174
FF (2) (5)	0.3773	0.3718	0.2527
HFL (2) (5)	0.5110	0.5419	0.3918
IRL (4) (5)	0.0847	0.0546	0.0630
LIT (3) (5)	0.1798	0.2218	0.1888
PTA (3) (7)	0.0371	0.0532	0.0929
UKL (4) (8)	-0.0545	-0.0074	0.0486

Notes:
(1) The Sharpe ratio is obtained dividing the mean return of the trading system by its standard deviation [see equation (5) 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.

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