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An empirical evaluation of non-linear trading rules

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ABSTRACT

In this paper we investigate the profitability of non-linear trading rules based on nearest neighbour predictors. Applying this investment strategy to the New York Stock Exchange, our results suggest that, taking into account transaction costs, the non-linear trading rule is superior to a risk-adjusted buy-and-hold strategy (both in terms of returns and of Sharpe ratios) for the 1998 and 1999 periods of upward trend. In contrast, for the relatively "stable" market period of 2000, we found that both strategies generate equal returns, although the risk-adjusted buy-and-hold strategy yields a higher Sharpe ratio.

JEL classification numbers: G10, G14, C53

KEY WORDS: Technical trading rules, Nearest neighbour predictors, Security markets

1. Introduction

In fundamental analysis forecast of future prices and returns are based upon economic fundamentals, such as dividends, interest, price-earning ratios, macroeconomic variables, etc.. In contrast, technical analysis looks for patterns in past prices and base its forecasts upon extrapolation of these patterns. The basic idea is that "prices moves in trends which are determined by changing attitudes of investors toward a variety of economic, monetary, political and psychological forces" (Pring, 1991, p. 2).

Although technical trading rules have been used in financial markets for over a century (see, e. g., Plummer, 1989), it is only during the last decade that technical analysis has regained the interest of the academic literature. Several authors have shown that financial prices and returns are forecastable to some extent, either from their own past or from some other publicly available information [see, e. g., Fama and French (1988), Lo and MacKinley (1988, 1997, 1999) and Pesaran and Timmerman (1995, 2000)]. Furthermore, surveys among market participant show that many use technical analysis to make decisions on buying and selling. For example, Taylor and Allen (1992) report that 90% of the respondents (among 353 chief foreign exchange dealers in London) say that they place some weight on technical analysis when forming views for one or more time horizons.

A considerable amount of work has provided support for the view that technical trading rules are capable of producing valuable economic signals in financial markets. Regarding stock markets, Brock *et al.* (1992) used bootstrap simulations of various null asset pricing models and found that simple technical trading rule profits cannot be explained away by the popular statistical models of stock index returns. Later, Gençay (1996 and 1998) found evidence of non-linear predictability in stock market returns by combining simple technical trading rules and feed-forward network (see also Fernández-Rodríguez, González-Martel and Sosvilla-Rivero, 2000).

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", etc.), which are highly non-linear and too complex to be expressed algebraically. Clyde and Osler (1997) show that the non-parametric, nearest neighbour (NN) forecasting technique can be viewed as a generalisation 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 Farmer and Sidorowich (1987) and Fernández-Rodríguez, Sosvilla-Rivero and Andrada-Félix (1997)]. 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. Implicit in the NN approach is the recognition that some price movements are significant (i. e., they contribute to the formation of a specific pattern) and others are merely random fluctuations to be ignored.

Since the NN approach to forecasting is closely related to technical analysis, we aim to combine these two lines of research (non-linear forecasting and technical trading rules) to assess the economic significance of the predictability in stock markets. To that end, in contrast with the previous papers, the (non-linear) predictions from NN forecasting methods are transformed into a simple trading strategy, whose profitability is evaluated against a simple buy-and-hold strategy. Furthermore, unlike previous empirical evidence when evaluating trading performance, we will consider transaction costs, as well as a wider set of profitability indicators than those usually examined. We have applied this investment strategy to the New York Stock Exchange (NYSE), using data for the 3 January 1966-29 December 2000 period (8812 observations).

The paper is organised as follows. Section 2 briefly presents the local NN predictors, while in Section 3 we show how the local predictions are transformed in a simple trading strategy and how we assess the economic significance of predictable patterns in the stock market. The empirical results are shown in Section 4. Finally, Section 5 provides some concluding remarks.

2. NN predictions

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 Farmer and Sidorowich (1987) and Fernández-Rodríguez, Sosvilla-Rivero and Andrada-Félix (1997)]. 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.

The NN forecast can be succinctly described as follows [see Fernández-Rodríguez, Sosvilla-Rivero and Andrada-Félix. (1999) for a more detailed account]:

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

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

   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

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

   most similar to the last available vector

$$x_T^m = \left(x_T, x_{T-1}, x_{T-2}, \ldots, x_{T-m+1}\right),$$

where $k=int(\lambda T)$ $(0<\lambda<1)$ with $int(\cdot)$ standing for the integer value of the argument in brackets, and where we use the subscript "i_j" (j=1,2,...,k) to denote each of the k chosen m-histories.

To that end, we look for the closest k vectors in the phase space $\Re^m$, in the sense that they maximise the function:

$$\rho\left(x_i^m, x_T^m\right)$$

(i.e., looking for the highest serial correlation of all m-histories, x_i^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:

$$\hat{x}_{T+1} = \hat{\alpha}_0 x_T + \hat{\alpha}_1 x_{T-1} + \ldots + \hat{\alpha}_{m-1} x_{T-m+1} + \hat{\alpha}_m$$

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

$$\sum_{r=1}^{k} (x_{i_r+1} - \alpha_0 x_{i_r} - \alpha_1 x_{i_r-1} - \ldots - \alpha_{m-1} x_{i_r-m+1} - \alpha_m)^2$$

Note that the NN predictors depend on the values of embedding dimension m and the number of closest k points in the phase space $\Re^m$.

3. Trading rules

The trading rule considered in this study is based on a simple market timing strategy, consisting of investing total funds in either the stock market or a risk free security. The forecast from NN predictors are used to classify each trading day into periods "in" (earning the market return) or "out" of the market (earning the risk-free rate of return). The trading strategy specifies the position to be taken the following day, given the current position and the "buy" or "sell" signals generated by the NN predictors. On the one hand, if the current state is "in" (i. e., holding the market) and the share prices are expected to fall on the basis of a sell signal generated by the NN predictor, then shares are sold and the proceeds from the sale invested in the risk free security [earning the risk-free rate of return $r_f(t)$]. On the other hand, if the current state is "out" and the NN predictor indicate that share market prices will increase in the near future, the rule returns a "sell" signal and, as results, the risk free security is sold and shares are bought [earning the market rate of return $r_m(t)$]. Finally, in the other two cases, the current state is preserved.

The trading rule return over the entire period of 1 to T can be calculated as:

$$r = \sum_{t=1}^{T} r_m(t)\; I_b(t) + \sum_{t=1}^{T} r_f(t)\; I_s(t) + n\; \log \frac{1-c}{1+c}$$

where $r_t = \log P_t - \log P_{t-1}$ is the market rate of return, P_t is the closing price (or level of the composite stock index) on day *t;* $I_b(t)$ and $I_s(t)$ are indicator variables equal to one is the NN signals buy and sell, respectively, and zero otherwise, satisfying the relation $I_b(t) x I_s(t) = 0$, $\forall t \in [1,T]$; n is the number of transactions; and c denotes the one-way transaction costs (expressed as a fraction of the price).

In order to assess profitability, it is necessary to compare the return from the trading rule based on the NN predictors to an appropriate benchmark. To that end, we construct a weighted average of the return from being long in the market and the return from holding no position in the market and thus earning the risk free rate of return. The return on this risk-adjusted buy-and-hold strategy can be written as

$$r_{bh} = \beta \sum_{t=1}^{T} r_m(t) + (1-\beta) \sum_{t=1}^{T} r_f(t) + 2\log\frac{1-c}{1+c}$$

where β is the proportion of trading days that the rule is in the market.

Therefore, the excess return from a trading rule based on the NN predictors is given by

$$\Delta r = r - r_{bh}$$

In the empirical implementation, we will modify the simple rule introducing a filter in order to reduce the number of false buy and sell signals by eliminating "whiplash" signals when the NN predictor at date *t* is around the closing price at *t-1*. This filtered rule will generate a buy (sell) signal at date *t* if the NN predictor is greater than (is less than) the closing price at *t-1* by a percentage δ of the standard deviation σ of the first difference of the price time series from *1* to *t-1*. Therefore, if $\hat{P}_t$ denotes the NN prediction for P_t:

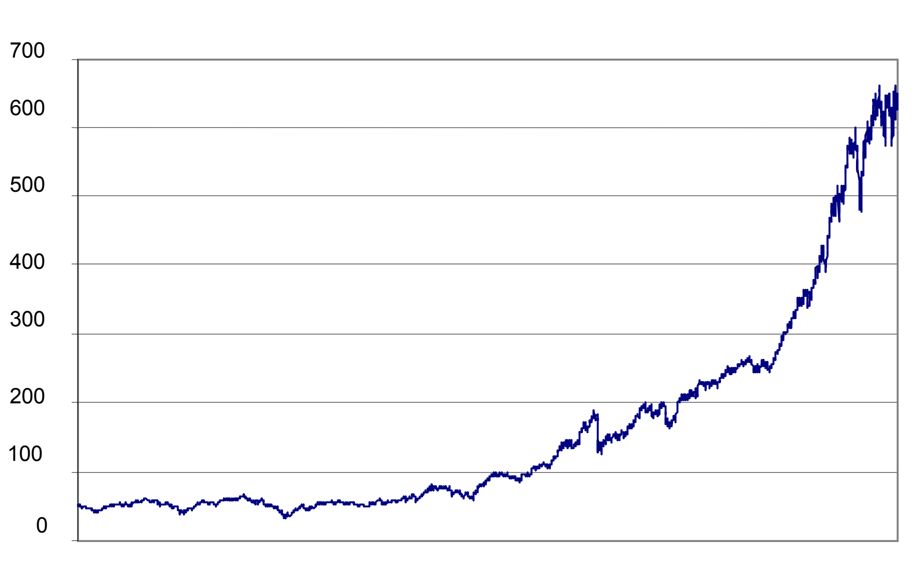
- If $\hat{P}_t > P_{t-1} + \delta\sigma$ and we are out the market, a buy signal is generated. If we are in the market, the trading rule suggest to continue holding the market.
- If $\hat{P}_t \le P_{t-1} - \delta\sigma$ and we are in the market, a sell signal is generated. If we are out of the market, we continue holding the risk free security.

4. Data and empirical results

4.1.Data

The data consists of the daily closing values of the NYSE Composite Index, which reflects the price of all common stocks listed on the Exchange. The data is collected over period 3 January 1966 to 29 December 2000, consisting of 8812 observations (see Figure 1). For the purpose of avoiding the possibility of data-snooping in the choice of time periods, we consider three successive training periods and report the summarised results for each case. In the first case, the in-sample training period runs from 3 January 1966 to 31 December 1997 and an out-of-sample test period covers from 2 January 1998 to 31 December 1998. In the second case, the in-sample training period runs from 3 January 1966 to 31 December 1998 and an out-of-sample test period covers from 4 January 1999 to 31 December 1999. Finally, in the third case, the in-sample training period runs from 3 January 1966 to 31 December 1999 and an out-of-sample test period covers from 3 January 2000 to 29 December 2000.

Figure 1: NYSE Composite Index



As can be seen in Figure 2, the NYSE Composite Index began 1998 at 511.19 and reached 39 new all-time highs before closing the year at a 595.81 (an increase of 16.6%). The index experienced a high degree of volatility: during the first part of the year significant increases were observed, followed by a outbreak of turbulence in the financial markets of emerging economies that wiped out almost all of the market gains through mid-July. However, sentiment in global financial markets changed once again during the last quarter of 1998, with the stock prices showing a significant recovery after the first week of October 1998. Regarding 1999, the NYSE Composite Index had a gain of 9.2% to close at 650.30, after reaching 20 new all-time highs (see Figure 3). Optimism about long-term earnings growth prospect for high-technology firms played an important role in this increase in stock prices. Finally, as shown in Figure 4, the NYSE Composite Index reached its record high of 677.58 on 1 September before closing the year at 656.87 (an increase of 1.01%). The implosion of Internet-related companies, high oil prices and a tighter Fed policy and uncertain political environment stemming from the prolonged Presidential election contributed to discontinue the upward trend that had been apparent from 1995 onwards.

Figure 2: NYSE Composite Index (1998)

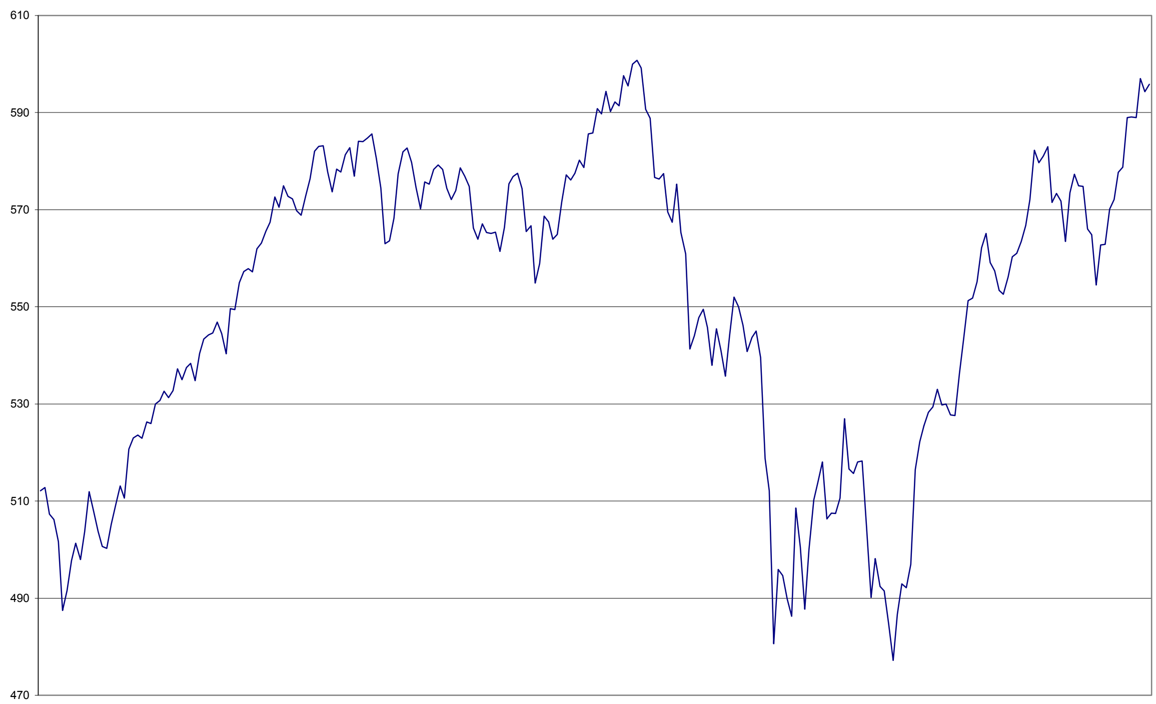


Figure 3: NYSE Composite Index (1999)

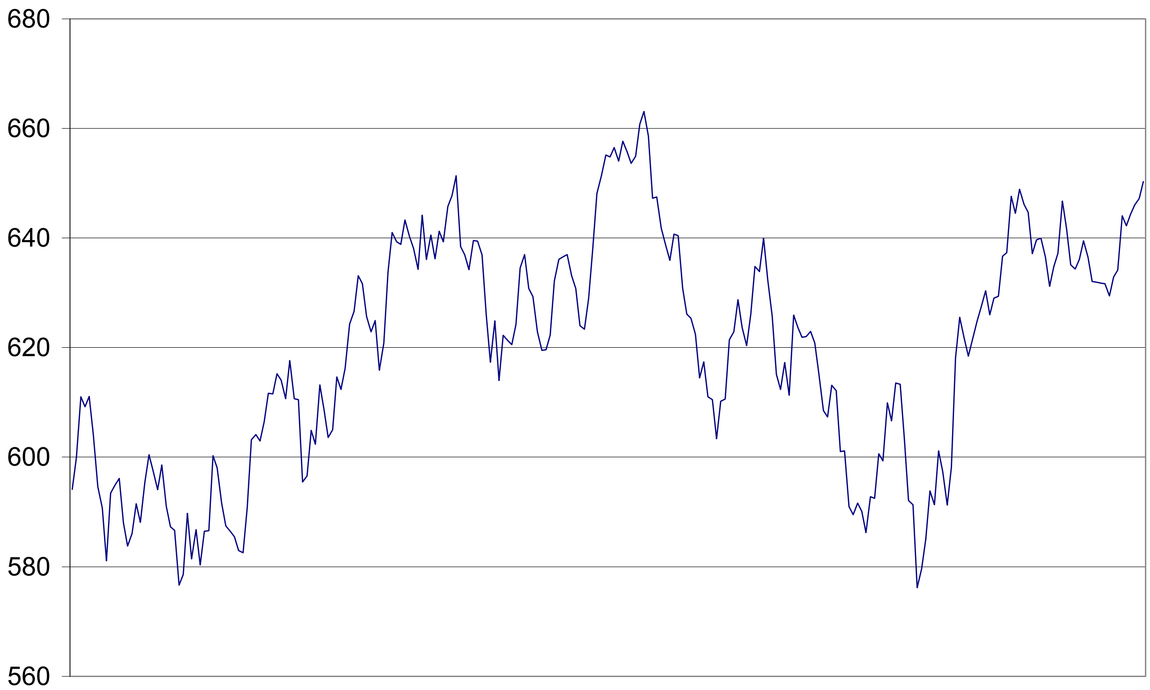
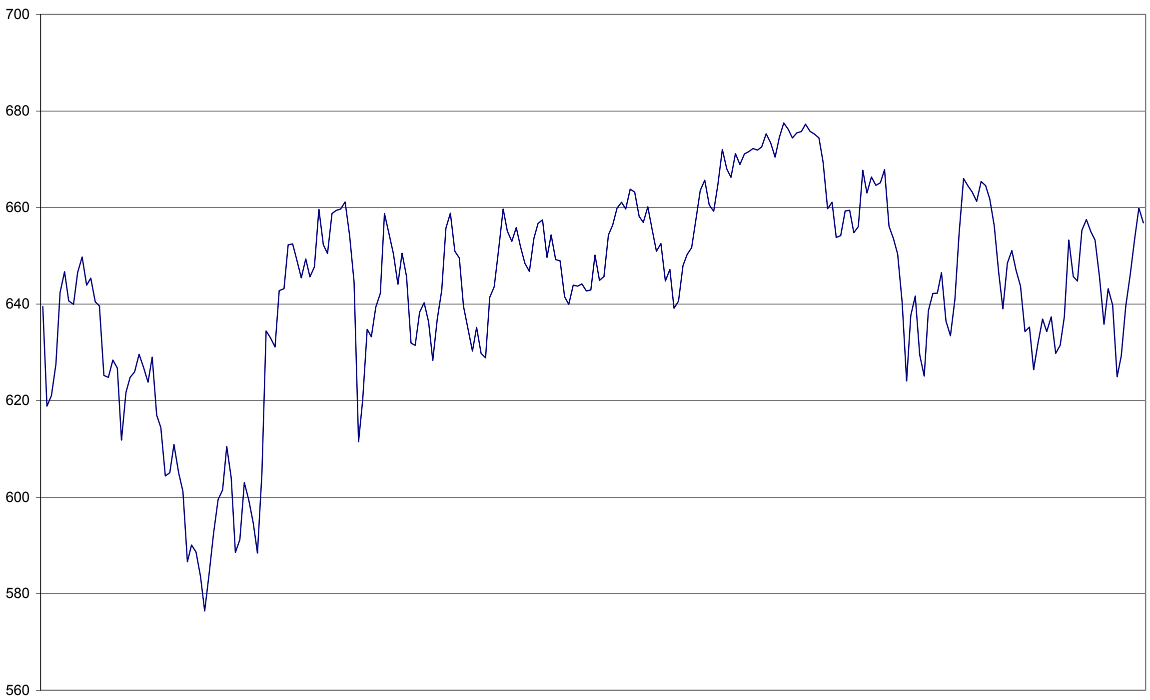


Figure 4: NYSE Composite Index (2000)



4.2. Results

Since our predictors depend on the values of embedding dimension *m* and the number of closest *k* points in the phase space $\Re^m$, we present the results for values of *m* of 2, 3 and 4 and for values of *k* of 130, 140 and 150. In addition, we also consider filters of 0.5 and 0.75. Given our previous empirical studies, these are reasonable values for the parameters.

Regarding the transaction costs, results by Sweeny (1988) suggest that large institutional investors could achieved in the mid-1970s one-way transaction costs in the range of 0.1-0.2%. Even thought there has been substantial reductions in costs in the last decades, we initially use one-way transaction costs of 0.15%. We also investigate the robustness of the results with transaction costs of 0.25%.

The out–of-sample excess return statistics with transaction costs of 0.15% are reported in Table 1. As can be seen, for a embedding dimension *m*=3 and filters of 0.50 and 0.75, we find non-negative excess returns for all out-of-sample periods considered (except for the last period with *k*=150). For the first period (1998), we also find positive excess returns with *m*=2 and a filter of 0.50, as well as with *m*=4 and a filter of 0.75. For the second period (1999), there is evidence of positive excess returns for *m*=2 and *k*=130 with a filter of 0.75. Finally, last forecasting period (2000), we also obtain positive excess returns with *m*=2 and *k*=150 when applying a filter of 0.50, for all *k* with a filter of 0.75, as well as for *m*=4 and *k*=130 with a filter of 0.75.

Table 1: Excess returns						
Transaction costs=0.15%						
A) 2 January 1998 to 31 December 1998						
	Filter = 0.50			Filter= 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	0.0987	0.0450	0.0673	-0.0613	-0.1021	-0.0613
m = 3	0.0917	0.1212	0.0922	0.1348	0.0796	0.0796
m = 4	-0.0322	-0.0322	-0.1061	0.1428	0.0040	0.0040
B) 4 January 1999 to 31 December 1999						
	Filter =0.50			Filter = 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	-0.0682	-0.0682	-0.0557	0.0158	0.0000	0.0000
m = 3	0.1054	0.0615	0.0533	0.0571	0.0695	0.0000
m = 4	-0.0164	-0.0182	-0.0298	-0.0107	-0.0171	-0.0214
C) 3 January 2000 to 29 December 2000						
	Filter = 0.50			Filter = 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	-0.0671	-0.0588	0.0510	0.0556	0.0556	0.0556
m = 3	0.0655	0.0254	-0.0067	0.0000	0.0000	0.0000
m = 4	-0.0779	-0.1014	-0.0438	0.0175	-0.0409	-0.0036

We investigate the impact of trading costs on the results by recalculating the excess return statistics using transaction costs of 0.25%. Table 2 presents the results. As can be seen, a similar pattern than in Table 1 emerges: in 17 out of the 18 cases considered, the trading strategy based on the non-linear predictors yields equal or higher returns than the risk-adjusted buy-and-hold strategy for a embedding dimension m=3, being the only exception the results from last period with a k=150 and a filter of 0.50. For the first forecasting period (1998), we also obtain positive excess returns with m=2 and a filter of 0.50, and with m=4 and a filter of 0.75. For the second period (1999), there is evidence of positive excess returns with m=2, k=130 and a filter of 0.75. Finally, for the last period (2000), we also find positive returns with m=2, k=150 and a filter of 0.50, with m=2 and a filter of 0.75, and m=4, k=130 and a filter of 0.75.

Table 2: Excess returns						
Transaction costs= 0.25%						
A) 2 January 1998 to 31 December 1998						
	Filter = 0.50			Filter= 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	0.0879	0.0360	0.0582	-0.0623	-0.1034	-0.0623
m = 3	0.0811	0.1128	0.0858	0.1313	0.0761	0.0761
m = 4	-0.0451	-0.0451	-0.1130	0.1395	0.0022	0.0022
B) 4 January 1999 to 31 December 1999						
	Filter =0.50			Filter = 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	-0.0753	-0.0753	-0,063	0.0141	0.0000	0.0000
m = 3	0.0907	0.0488	0.0425	0.0541	0.0642	0.0000
m = 4	-0.0276	-0.0270	-0.0369	-0.0124	-0.0189	-0.0232
C) 3 January 2000 to 29 December 2000						
	Filter = 0.50			Filter = 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	-0.0823	-0.0722	0.0437	0.0550	0.0550	0.0550
m = 3	0.0485	0.0081	-0.0202	0.0000	0.0000	0.0000
m = 4	-0.0930	-0.1121	-0.0546	0.0141	-0.0451	-0.0066

According to the results in Tables 1 and 2, it appears that a strategy of using *m*=3 and a filter of 0.75 could be recommended for practitioners when applying this non-linear trading rule.

Given that individuals are generally risk averse, besides the excess return, we also consider the Sharpe ratio (Sharpe, 1966). This is a risk-adjusted return measure given by:

$$RS = \frac{\overline{r}}{\sigma}$$

where $\overline{r}$ is the average annualised return of the trading strategy and σ is the standard deviation of daily trading rule returns. As can be seen, the higher the Sharpe ratio, the higher the mean annual net return and the lower the volatility.

Tables 3 and 4 shows the results for the trading rule based on the NN predictor, using transaction costs of 0.15% and 0.25%, respectively. Table 5 presents the Sharpe ratio for the risk-adjusted buy-and-hold strategy. For the first and last out-of-sample periods (1998 and 2000, respectively), the NN-based trading rule yields higher Sharpe ratios than the risk-adjusted buy-and-hold strategy in 9 out of 18 cases considered, while for the second period (1999), in 6 out of the 18 cases the non-linear trading rule generates higher Sharpe ratios than those from the benchmark strategy. It is interesting to note that these results are robust to the transaction costs assumed in the calculations (0.15% or 0.25%). Furthermore, it should be observed that for our recommended parameters (m=3 and a filter of 0.75), the non-linear trading rule performs relatively well with respect to the alternative strategy, both in the fist and second periods (3 out of 3 cases and 2 out of 3 cases, respectively).

Table 3: Sharpe ratios:
NN-based trading rule
Transaction costs = 0.15%

A) 2 January 1998 to 31 December 1998						
	Filter = 0.50			Filter =0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	0.0998	0.0636	0.0735	0.0142	-0.0075	0.0142
m = 3	0.0904	0.1023	0.0880	0.1245	0.0860	0.0860
m = 4	0.0373	0.0373	-0.0011	0.1122	0.0409	0.0409
B) 4 January 1999 to 31 December 1999						
	Filter =0.50			Filter = 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	-0.0022	-0.0022	0.0039	0.0716	0.0000	0.0000
m = 3	0.0918	0.0699	0.0663	0.0708	0.0896	0.0000
m = 4	0.0321	0.0266	0.0215	0.0466	0.0435	0.0360
C) 3 January 2000 to 29 December 2000						
	Filter = 0.50			Filter = 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	-0.0139	-0.0068	0.0504	0.0441	0.0441	0.0441
m = 3	0.0626	0.0416	0.0279	0.0000	0.0000	0.0000
m = 4	-0.1624	-0.0265	-0.0028	0.0450	-0.0049	0.0231

Table 4: Sharpe ratios						
NN-based trading rule						
Transaction costs = 0.25%						
A) 2 January 1998 to 31 December 1998						
	Filter = 0.50			Filter = 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	0.0941	0.0592	0.0689	0.0134	-0.0083	0.0134
m = 3	0.0853	0.0982	0.0849	0.1225	0.0840	0.0840
m = 4	0.0300	0.0300	-0.0046	0.1103	0.0397	0.0397
B) 4 January 1999 to 31 December 1999						
	Filter =0.50			Filter = 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	-0.0071	-0.0071	-0.0015	0.0692	0.0000	0.0000
m = 3	0.0835	0.0626	0.0599	0.0683	0.0851	0.0000
m = 4	0.0235	0.0214	0.0161	0.0442	0.0412	0.0335
C) 3 January 2000 to 29 December 2000						
	Filter = 0.50			Filter = 0.75		
	k=130	k = 140	k = 150	k=130	k = 140	k = 150
m = 2	-0.0237	-0.0168	0.0462	0.0432	0.0432	0.0432
m = 3	0.0521	0.0309	0.0190	0.0000	0.0000	0.0000
m = 4	-0.0236	-0.0314	-0.0078	0.0421	-0.0071	0.0206

Table 5: Sharpe ratios:		
risk-adjusted buy-and-hold strategy		
	Transaction costs = 0.15%	Transaction costs = 0.25%
A) 3 January 1998 to 31 December 1998	0.0702	0.0687
B) 4 January 1999 to 31 December 1999	0.0570	0.0546
C) 3 January 2000 to 29 December 2000	0.0124	0.0112

5. Concluding remarks

The purpose of our paper has been to contribute to the debate on the relevance of non-linear forecasts of high-frequency data in financial markets. To that end, we have presented the results of applying the nearest neighbour (NN) predictors introduced by Farmer and Sidorowich (1987) and in Fernández-Rodríguez, Sosvilla-Rivero and Andrada-Félix (1997) to the New York Stock Exchange (NYSE), using data for the 3 January 1966-29 December 2000 period. This NN predictors have been transformed into a simple trading strategy, whose profitability is evaluated against a risk-adjusted buy-and-hold strategy. In doing so, our approach incorporates the essence of technical analysis: to identify approach regularities in the time series of prices by extracting non-linear patterns from noisy data. Furthermore, unlike previous empirical evidence, when evaluating trading performance, we have considered transaction costs, as well as a wider set of profitability indicators than those usually examined.

The main results are as follows. The NN-based trading rule is superior to a risk-adjusted buy-and-hold strategy (both in terms of returns and of Sharpe ratios) for the 1998 and 1999 periods of upward trend. In contrast, for the relatively "stable" market period of 2000, we found that both strategies generate similar returns, although the risk-adjusted buy-and-hold strategy yields a higher Sharpe ratio.

Our results suggest that a strategy of using an embedding dimension m=3 and a filter of 0.75 could be recommended for practitioners when applying this non-linear trading rule.

Therefore, the results in this paper indicate that the potential exists for investors to generate excess returns in stock markets by adopting a technical trading rules based on NN predictors.

References:

Brock, W., Lakonish, J. and B. LeBaron (1992). “Simple technical rules and the stochastic properties of stock returns”, *Journal of Finance*, Vol. 47, 1731-1764.

Clyde, W. C. and C. L. Osler (1997) "Charting: Chaos theory in disguise?", *Journal of Future Markets*, Vol. 17, 489-514.

Fama, E. and French, K. (1988): “Dividends yield and expected stock returns”, *Journal of Financial Economics*, Vol. 22, 3-27.

Farmer, D. and J. Sidorowich, 1987, Predicting chaotic time series, *Physical Review Letters*, Vol. 59, 845-848.

Fernández-Rodríguez, F., González-Martel, C. and Sosvilla-Rivero, S. (2000): On the profitability of technical trading rules based on artifitial neural networks: Evidence from the Madrid stock market, *Economics Letters*, Vol. 61, 89-94.

Fernández-Rodríguez, F., Sosvilla-Rivero, S. and García-Artiles, M. D. (1997): "Using nearest neighbour predictors to forecast the Spanish stock market", *Investigaciones Económicas*, Vol. 21, 75-91.

Fernández-Rodríguez, F., Sosvilla-Rivero, S. and García-Artiles, M. D. (1999): "Dancing with bulls and bears: Nearest-neighbour forecasts for the Nikkei Index", *Japan and the World Economy*, Vol. 11, 395-413.

Fernández-Rodríguez, F., Sosvilla-Rivero, S. and Andrada-Félix, J. (1999): “Exchange-rate forecasts with simultaneous nearest-neighbour methods: Evidence from the EMS”, *International Journal of Forecasting*, Vol. 15, 383-392.

Gençay, R. (1996) "Nonlinear prediction of security returns with moving average rules", *Journal of Forecasting*, Vol. 15, 165-174.

Gençay, R. (1998) "The predictability of securities returns with simple technical rules", *Journal of Empirical Finance*, Vol. 5, 347-359.

Lo, A. W. and MacKinley, A. C. (1988): “Stock market prices do not follow random walks: Evidence from a simple specification test”, *Review of Financial Studies*, Vol. 1, 41-66.

Lo, A. W. and MacKinley, A. C. (1997): “Maximizing predicibility in stock and bonds markets”, *Macroeconomic Dynamics*, Vol. 1, 102-134.

Lo, A. W. and MacKinley, A. C. (1997): *A non-random walk down Wall Street.* Princeton University Press, Princeton.

Pesaran, M. H. and Timmerman, A. (1995): “Predictability of stock returns: Robustness and economic significance”, *Journal of Finance,* Vol. 50, 1201-1228.

Pesaran, M. H. and Timmerman, A. (2000): "A recursive modelling approach to predicting UK stock returns", *Economic Journal*, Vol. 110, 159-191.

Plummer, T. (1989), *Forecasting financial markets: The truth behind technical analysis*, Kogan Page, London.

Pring, M. J. (1991), *Technical analysis explained : The successful investor's guide to spotting investment trends and turning points*, Macgraw-Hill, New York.

Sweeney, R. J. (1988): "Some new filter rule tests: Methods and results". *Journal of Financial and Quantitative Analysis*, Vol. 23, 285-300.

Taylor, M. P. and Allen, H. (1992). "The use of technical analysis in the foreign exchange market". *Journal of International Money and Finance*, Vol. 11, 304-314.

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