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Further evidence on technical analysis and profitability of foreign exchange intervention*

by

Simón Sosvilla-Rivero**

Julián Andrada-Félix***

Fernando Fernández-Rodríguez****

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** FEDEA and Universidad Complutense de Madrid

*** Universidad de La Laguna

**** Universidad de Las Palmas de Gran Canaria

Abstract

In this paper we present new evidence on the positive correlation between returns from technical trading rules and periods of central bank intervention. To that end, we evaluate the profitability of a trading strategy based on nearest-neighbour (nonlinear) predictors, which may be viewed as a generalisation of graphical methods widely used in financial markets. We use daily data on the US Dollar/Deutsche mark and US Dollar/Japanese Yen covering the 1 February 1982-31 December 1996 period. Our results suggest that the exclusion of days of US intervention implies a substantial reduction in all profitability indicators (net returns, ideal profit measure, Sharpe ratio and directional forecast), being the reduction grater in the US Dollar-Deustchmark case than in the US Dollar-Japanese yen case.

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KEY WORDS: Central bank intervention, Technical trading rules, Exchange rates

1. Introduction

Technical analysis involves using charts of financial price movements in order 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 financial markets.

In particular, recent research have discovered that excess returns from extrapolative technical trading rules in foreign exchange markets are high during periods of central bank intervention [see, e. g., LeBaron (1996), Szakmary and Weller (1997) and Neely and Weller (1997)].

This empirical evidence has largely limited its attention to the moving average (MA) rule, which is easily expressed algebraically. According to this trading rule, buy and sell signals are generated by two moving averages of the level of the exchange-rate series: a long-period average and a short-period average. A typical moving average trading rule prescribes a buy (sell) when the short-period moving average crosses the long-period moving average from below (above) [i. e. when the original time series is rising (falling) relatively fast].

The fact that this information could be used in a profitable trading strategy would imply that technical analysis based on this MA rules are able to extract some information concerning the hidden structure of the data generation process of the exchange rate series, which is "too complex, short-term or nonlinear to be captured adequately by the current state of financial economics" (Taylor, 1991, 15).

Nevertheless, practitioners relay heavily on many other techniques, including a broad category of graphical methods ("heads and shoulders", "resistance/support levels", etc.), which are highly nonlinear and complex to be expressed algebraically. Clyde and Osler (1997) show that the nonlinear nearest neighbour (NN) forecasting technique, based on the literature on complex dynamic systems, can be viewed as a generalization of these graphical methods. The basic idea behind these predictors is 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.

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 of the European Monetary System. 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 latter finding is a first sight in line with the graphical methods practices. Typically, charts are not used to make point prediction, instead they are used to give some indication on the direction of future movements of the underlying series.

In this paper we will try to provide some additional evidence on the positive correlation between returns from technical trading rules and periods of central bank intervention. To that end, in contrast with the previous papers, the predictions from NN forecasting methods are transformed into a simple trading strategy, whose profitability is evaluated both over the entire sample period and after removing those days where intervention takes place. Furthermore, unlike previous empirical evidence, when evaluating trading performance, we will consider both interest rates and transaction costs, as well as a wider set of profitability indicators than those usually examined.

We have applied this investment strategy to the US Dollar exchange rate, using daily noon (Eastern time) buying rates in New York city vis-à-vis the Deustchmark and the Japanese yen. When evaluating returns in excess of nominal interest rates, we use daily overnight interest rates collected by the Bank for International Settlements at 9:00 a. m. (GMT). Finally, we utilize daily US intervention data, in millions of US dollars, released by the Federal Reserve System. Our data set covers the 1 March 1973-31 December 1996 period, except for the interest rate data that refers to the 1 February 1982-31 December 1996 period.

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 forecasting methods

Let x_t (t=1,...,N) 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_{N+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:

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

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 divide the series x_t^m into two parts, the *fitting set* $F = x_{n_f}^m = (x_1, x_2, \ldots, x_{n_f})$ and the *testing set* $T = (x_{n_f1}, x_{n_f2}, \ldots, x_{n_fn_t})$, with $n_f + n_t = N - (m-1)$.

Then we consider the k m-histories

$$x_{i_1}^m, x_{i_2}^m, x_{i_3}^m, \ldots, x_{i_k}^m, \qquad (2)$$

most similar to the last available vector $x_{n_f}^m$, where $k \equiv \lambda N$ $(0<\lambda<1)$, 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. To establish NNs to F, one looks for the closest k vectors [expression (2)] in the phase space $\mathbb{R}^m$, in the sense that they maximise the function:

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

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

Finally, once the nearest neighbours to $x_{n_f}^m$ have been established, we consider predictors of the future evolution of $x_{n_f}^m$. Let $\hat{x}_{n_f+1}$ be a predictor of x_{n_f+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:

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

The fitting set $x_{n_f}^m$ is updated, that is for each m-history in the testing set $x_j \in T$, the serial correlation of all m-histories are computed and the k nearest neighbours $x_i^m \in F$, are determined. For every $x_i^m \in F$, we considering the following local regression model:

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

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

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

3. Empirical results

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:

$$R^t_T = \sum^n_{i=1} y_t \ r_t \tag{7}$$

where r_t is the return from a foreign currency position over the period $(t, \ t+1)$, y_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:

$$r_t = ln \ (E_{t+1}) \text{ - } ln(E_t) \text{ - } ln \ (1+i_t) \ + \ ln \ (1+i^*_t) \tag{8}$$

where E represents the spot dollar price of foreign exchage, i is the US daily interest rate and i^* is the foreign 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:

$$R^n_T = \sum^n_{i=1} y_t \ r_t \text{ - } \ nrt \ \{ln(1\text{-}c) \text{ - } ln(1+c)\} \tag{9}$$

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:

$$R^n_B = ln \ (E_{t+\eta}) \text{ - } ln(E_t) \ \text{ - } \{ln(1\text{-}c) \text{ - } ln(1+c)\} \tag{10}$$

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

The estimated total and net returns are calculated by:

$$R^t_T = \sum^{n+\eta+1}_{i=n+1} \hat{y}_t \, r_t \tag{11}$$

and

$$R^n_T = \sum^{n}_{i=1} \hat{y}_t - nrt \, \{ln(1\text{-}c) - ln(1+c)\} \tag{12}$$

where $\hat{y}_t$ is the estimated recommended position for the tth observation. The estimation of $\hat{y}_t$ is carried out by the NN predictors. Regarding the transaction costs, following Levich and Thomas (1995) and Osler and Chang (1995), we consider a one-way cost of 0.025%.

Besides the total and net returns, we also consider other three profitability indicators: the sign predictions, the ideal profit and the Sharpe ratio. The sign predictions measure the percentage of times the trading rule assigns the correct buy or sell decision in accord with the sign of the corresponding return of a given period. A value higher than 50 would indicate a better accuracy than the random walk in predicting the direction of exchange rate movements. The ideal profit measures the returns of the trading system against a perfect predictor and is calculated by:

$$R_I = \frac{\sum_{t=n+1}^{n+\eta+1} \hat{y}_t r_t}{\sum_{t=n+1}^{n+\eta+1} |r_t|} \tag{13}$$

According to equation (13), $R_I = 1$ if the indicator variable $\hat{y}_t$ 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:

$$S_R = \frac{\mu_{\hat{R}_T}}{\sigma_{\hat{R}_T}} \tag{14}$$

According to equation (14), the higher the Sharpe ratio, the higher the return and the lower the volatility.

Finally, we have also computed the number of buy and sell signals generated (denoted N(buy) and N(sell), respectively), as well as the standard deviations of returns from buy signals, from sell signals and from both buy signals and sell signals (denoted σ_B, σ_S and σ_T, respectively).

Table 1 reports the estimated results over the entire forecasting period. As can be seen, the technical strategy generates 35% net returns for the US Dollar-Deustchmark exchange rate, whereas the buy-and-hold net return remains at -1.4%. For the US Dollar-Japanese yen case, the trading strategy net return and the buy-and-hold net return are 28% and -0.4%, respectively. Therefore, it seems technical trading returns dominate the buy-and-hold returns, showing the potential usefulness of nearest neighbour predictors for technical trading rules to forecast daily exchange data

As shown in Table 1, the sign predictions for the recommended positions are 53% and 52% for the US Dollar-Deustchmark and the US Dollar-Japanese yen exchange rates, respectively, clearly outperforming the random walk directional forecast. Regarding the ideal profit measure, it is always greater than zero and approximately 0.07 for both exchange rates. As for the Sharpe ratio, they are also similar in order (around 0.05), suggesting that risk/return ratios are similar across these exchange rates.

It is interesting to note that 1.08% more sell signals are generated than buys for the US Dollar-Deustchmark exchange rate, while for the US Dollar-Japanese yen case the trading rule generates 5.01% more buy signals than sells.

Furthermore, whereas in the US Dollar-Deustchmark case the standard deviation of total returns in all cases considered (i. e., from buy signals, from sell signals, and from both buy signals and sell signals), for the US Dollar-Japanese yen exchange rate the total returns from buy (sell) signals show a lower (higher) volatility than the total returns from both buy signals and sell signals.

To investigate the claim that central bank intervention in foreign exchange markets is a potential explanation for the profitability of technical trading rules, we follow LeBaron (1996)'s procedure and selectively examine the trading rule results after removing those returns from day t to $t+1$ for which intervention was non-zero on day t. Table 2 shows the results of the rule when excluding days of US intervention.

As can be seen by comparing Tables 1 and 2, there is some evidence that the returns are lower when there is not intervention in day t: the net returns from the trading strategy is now negative (-10% for the US Dollar-Deustchmark case and -28% for the US Dollar-Japanese yen case) whereas the buy-and-hold net return remains the same. In addition, there is a significant reduction in both the ideal profit measure and the Sharpe ratio (-37% for the US Dollar-Deustchmark case, and -49% for the US Dollar-Japanese yen case).

As for the sign predictions, there is also a reduction in the accuracy in predicting the direction of exchange rate movements, grater in the US Dollar-Deustchmark case (-2.26 percentage points) than in the US Dollar-Japanese yen case (-0.19 percentage points).

Finally, fewer buy and sell signals are now generated than before for both exchange rates, generating the trading rule in absence of intervention more buy signals than sells (4,02% and 7.38% for the US Dollar-Deustchmark and the US Dollar-Japanese yen, respectively). Furthermore, the exclusion of days of US intervention implies an increase in all the volatility indicators for the total returns.

4. Concluding remarks

In this paper have provided some additional evidence on the claim that excess returns from extrapolative technical trading rules in foreign exchange markets are high during periods of central bank intervention. To that end, and unlike previous papers, we have evaluate the profitability of NN predictions considering both interest rates and transaction costs. This NN predictions, that can be thought as a generalization of graphical methods widely used in financial markets, have been applied to daily US Dollar exchange rates vis-à-vis the Deustchmark and the Japanese yen, over the 1 February 1982-31 December 1996 period.

The main results are as follows. Firstly, when profitability was evaluated for the entire forecasting period, the results suggest that using NN predictors as a trading rule generates net returns that dominate the buy-and-hold net returns. Furthermore, when computing the percentage of correct predictions, the trading rule based on the NN predictors shows always a value higher than 50%, clearly outperforming the random walk directional forecast. Finally, both the ideal profit measure and the Sharpe ratio are greater than zero and similar in order (0.07 and 0.05, respectively) for both exchange rates.

Secondly, when excluding days of US intervention there is a substantial reduction in all profitability indicators. The net returns from the trading strategy fall from 0.35% to -10% for the US Dollar-Deustchmark case, and from 0.30% to -28% for the US Dollar-Japanese yen case. In addition, there is a significant reduction in the ideal profit measure, the Sharpe ratio and in the directional forecast, being the reduction grater in the US Dollar-Deustchmark case than in the US Dollar-Japanese yen case. Finally, in absence of intervention fewer buy and sell signals are generated, and there is an increase in the volatility of the total returns regardless they refer to buys signals, sell signals or both buy signals and sell signals.

Therefore, our results indicate that there is a positive correlation between returns from technical trading rules and periods of central bank intervention, suggesting that central bank intervention in foreign exchange markets may be a potential explanation for the profitability of technical trading rules.

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TABLE 1: Results for the entire forecasting period (1)

Tests	US Dollar-Deustchmark exchange rate	US Dollar-Japanese yen exchange rate
Total return (2)	1.2799	1.2008
Net return (3)	0.3504	0.2793
Sign predictions (4)	52.88	51.60
Ideal profit ratio (5)	0.0666	0.0697
Sharpe ratio (6)	0.0496	0.0503
Buy and hold return (7)	-0.0139	-0.0044
N(buy) (8)	1849	1888
N(sell) (9)	1869	1798
σ_T (10)	0.0069	0.0065
σ_B (11)	0.0070	0.0062
σ_S (12)	0.0069	0.0067

Notes: (1) Forecasting period: 1-2-1982 to 31-12-1996.
(2) Returns generated by the trading rule over the forecast sample, before transaction fees are taken into account [see equation (11) in the text].
(3) Returns generated by each forecasting method over the forecast sample, after transaction fees are taken into account [see equation (12) in the text].
(4) Percentage of correct forecast direction.
(5) The ideal profit measures the returns of the trading system against a perfect predictor [see equation (13) in the text].
(6) The Sharpe ratio is obtained dividing the mean return of the trading system by its standard deviation [see equation (14) in the text].
(7) Returns generated using equation (10) in the text, where transaction fees are taken into account
(8) "N(buy)" is the number of buy signals generated by the rule.
(9) "N(sell)" is the number of sell signals generated by the rule.
(10) σ_T is the standard deviation of total returns from both buy signals and sell signals.
(11) σ_B is the standard deviation of total returns from buy signals.
(12) σ_S is the standard deviation of total returns from sell signals.

TABLE 2: Results when excluding days of US intervention (1)

Tests	US Dollar-Deustchmark exchange rate	US Dollar-Japanese yen exchange rate
Total return (2)	0.7706	0.5879
Net return (3)	-0.1012	-0.2836
Sign predictions (4)	50.62	51.41
Ideal profit ratio (5)	0.0420	0.0357
Sharpe ratio (6)	0.0308	0.0250
Buy and hold return (7)	-0.0139	-0.0040
N(buy) (8)	1747	1805
N(sell) (9)	1740	1681
σ_T (10)	0.0072	0.0067
σ_B (11)	0.0071	0.0066
σ_S (12)	0.0073	0.0069

Notes: (1) Forecasting period: 1-2-1982 to 31-12-1996.
(2) Returns generated by the trading rule over the forecast sample, before transaction fees are taken into account [see equation (11) in the text].
(3) Returns generated by each forecasting method over the forecast sample, after transaction fees are taken into account [see equation (12) in the text].
(4) Percentage of correct forecast direction.
(5) The ideal profit measures the returns of the trading system against a perfect predictor [see equation (13) in the text].
(6) The Sharpe ratio is obtained dividing the mean return of the trading system by its standard deviation [see equation (14) in the text].
(7) Returns generated using equation (10) in the text, where transaction fees are taken into account
(8) "N(buy)" is the number of buy signals generated by the rule.
(9) "N(sell)" is the number of sell signals generated by the rule.
(10) σ_T is the standard deviation of total returns from both buy signals and sell signals.
(11) σ_B is the standard deviation of total returns from buy signals.
(12) σ_S is the standard deviation of total returns from sell signals.

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