SPECULATIVE STRATEGIES IN THE FOREIGN EXCHANGE MARKET BASED ON GENETIC PROGRAMMING PREDICTIONS

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ABSTRACT

In this paper, we investigate the out-of-sample forecasting ability of a genetic program to approach the dynamic evolution of the Yen/US$ and Pound Sterling/US$ exchange rates, and verify whether the method can beat the random walk model. Later on, we use the predicted values to generate a trading rule and we check the possibility of obtaining extraordinary profits in the Foreign Exchange Market. Our results reveal a slight forecasting ability for one-period-ahead which is lost when more periods ahead are considered. On the other hand, our trading strategy obtains above-normal profits. However, when transaction costs are incorporated, the profits practically disappear or become negative.

Keywords: Genetic Programming, Exchange Rate Forecasting, Foreign Exchange Market Trading Strategies

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I-. Introduction

The Foreign Exchange Market constitutes the biggest financial market in the world. This fact explains why exchange rate modeling and forecasting has become for a long time a recurrent focal issue for academic researchers and practitioners. In spite of the effort made for understanding and predicting its evolution, it is widely assumed that the exchange rate evolves in a very complex, unpredictable and apparently erratic way. These dynamic features allow corroborating the well-known Efficient Market Hypothesis (Fama, 1970). According to the weak version of this assumption, the exchange rate reflects all the information which can be obtained from its own past values. Two direct consequences can be derived from the acceptation of this hypothesis. Firstly, the exchange rates follow a random walk process and, secondly, no profitable trading strategies can be implemented. Many authors have empirically demonstrated that foreign exchange rates, just like other financial time series, are well approximated by a random walk model (Mussa, 1979). For example, in the competition realized by Meese and Rogoff (1983), it was shown that the majority of the structural and time series models could not improve the out-of-sample predictions of a simple random walk. Moreover, the hypothesis also implies that investors cannot obtain any extraordinary and persistent profit from a trading rule that decided when to buy or when to sell a currency based exclusively on past values of the exchange rate.

Recent theoretical and empirical results seem to support the growing belief that the behaviour of the exchange rates includes some nonlinear deterministic component (Hsieh, 1989; Brooks, 1996; Serletis and Gogas, 2000; Kocenda, 2001). If the presence of these nonlinear structures was important, it would be possible to improve significantly the forecasting accuracy using nonlinear methods and generate profitable trading strategies. Some authors, like Fernández-Rodríguez and Sosvilla-Rivero (1998), provide evidence to support the non-linear prediction of exchange rates. It is also recognised that trading rules based on sophisticated forecasting methods are able to exploit certain hidden nonlinear structures and achieve extraordinary profits in the Foreign Exchange Market (Tenti, 1996).

The research carried out by Takens (1981) and Casdagli (1989), among many others, have contributed to develop the methodology required for non-linear time series modeling and analysis. Specifically, Takens' Theorem establishes that, given a deterministic time-series, $\{x_t\}_{t=1}^{N}$, there exists a function, $F:\Re^m \rightarrow \Re$, such that

$$x_t = F(x_{t-\tau}, x_{t-2\tau}, ..., x_{t-m\tau}) \qquad (1)$$

where τ and m are parameters depending on the time series, technically called delay factor and embedding dimension, respectively. Therefore, the theorem demonstrates that past values can explain the future behaviour of a variable if the time series is deterministic. The problem to be solved is how to find a good functional representation of the true but unknown dynamic $F(\cdot)$.

Many non-linear models attempt to approximate $F(\cdot)$ considering a parametric point of view. Therefore, aprioristic and specific non-linear functional forms are assumed. For example, the bilinear and autoregressive exponential models have been employed in exchange rates forecasting (Drunat et al. 1998). However, the functional form of these nonlinear models is discretionally imposed by the researcher rather than observed in the data, leading to a possible misspecification problem. Moreover, as Diebold and Nason

(1990) point out, the nonlinear and parametric perspective only takes into account a very scarce number of structures among all possible nonlinear relationships which could govern the exchange rate dynamic.

The growth of computer power has allowed a significant development, improvement and intense use of nonlinear and nonparametric techniques for the functional approach to $F(\cdot)$. During the last decade, applied econometricians have incorporated all these techniques into their toolbox to analyse and predict financial time series, including exchange rates forecasting. At the beginning, the most common nonparametric method in exchange rates forecasting consisted in the application of different generalizations of the standard nearest neighbour technique (Diebold and Nason 1990; Meese and Rose, 1991; Bajo- Rubio et al., 1992; Lisi and Medio, 1997). Later on, an intense and popularized use of neural networks was observed (Kuan and Liu, 1995; Hann and Steurer, 1996; Lubecke et al., 1998; Plasmans et al., 1998; Zhang and Hu, 1998; Franses and Homelen, 1998; Zhang and Hu, 1998; Walzack, 2001). Moreover, many papers carried out not only a forecasting exercise using neural networks, but also they constructed trading strategies based on the obtained predictions (Rawani et al., 1993; Tenti, 1996; Franses and Griensven, 1998, Gençay, 1999; Hu et al. 1999; Yao and Tan, 2000).

Recently, an additional functional search procedure based on Darwinian theories of natural selection and the survival of the fittest has been incorporated to solve the exchange rates forecasting problem (Álvarez-Díaz and Álvarez, 2003), and to generate trading strategies in the Foreign Exchange Market (Neely et al., 1997). These procedures, called genetic programming (Koza, 1992), have already demonstrated empirically their robustness in nonlinear time series analysis and, specifically, in approaching complex dynamics (Szpiro, 1997; Yadavalli et al., 1999; Álvarez et al., 2001). Moreover, they offer many advantages in comparison with forecasting methods previously employed. Firstly, they do not assume any a-priori and discretional hypothesis on the functional form of the model; therefore, it is possible to obtain models in which "data speak for themselves". Secondly, they are more robust and easy-to-use than neural networks. Finally, regarding nearest neighbour, they offer explicitly a mathematical equation which maybe optimal in approximating the true but unknown dynamic $F(\cdot)$. In this way, genetic programming provides more direct knowledge of functional relations between past, present and future values of the time series. As opposed to these advantages, they usually have the difficulty of being computationally intensive. Nevertheless, given their advantages as well as their strong forecasting power, a greater use of these techniques in finance and economics is anticipated (Wong and Bodnovich, 1998; Kaboudan, 2000).

In this paper, we use a genetic program (GP) to approach the function $F(\cdot)$ in the specific case of the weekly exchange rate of the Japanese Yen and the Pound Sterling (BP) against the US Dollar. The pursued objective in this study is two-fold. First of all, we verify whether or not GP can produce better predictions than those obtained by a random walk. Secondly, we use the generated predictions to construct a trading strategy and determine whether we can obtain above-normal profits in the foreign exchange markets.

The article is presented as follows. After this introduction, Section 2 presents the forecast technique used in our study. In Section 3, certain important aspects of the forecasting exercise and the strategy simulation are commented on. The results obtained are presented in Section 4, considering point prediction, sign prediction and the economic value of the predictions. Finally, in Section 6 we draw our conclusions.

II-. Genetic Programming

Genetic Algorithms, originally developed by Holland (1975) and later spread by Goldberg (1989) and Mitchell (2001), enclose a whole series of computing procedures inspired in biological concepts based on the Theory of Evolution of Species*:* survival of the fittest individuals, reproduction and birth of offspring with a good genetic heritage. The basic characteristic of these procedures is to use some evolutionary rules observed in Nature as inspiration for solving certain mathematical optimization process. Specifically, from the evolution of a random set of possible solutions and by means of applying operators based on natural selection concepts, these methods allow finding a good approximation to the solution of different optimization problems, including modeling issues.

In the specialized literature there is not a definition commonly accepted of genetic algorithms which allows us to distinguish them from other computational evolutionary techniques. However, there exist many programs considered as genetic algorithms which present the following common elements: initial population of possible solutions to the problem, selection process using some fit criterion, and use of crossover and random mutation to generate new solutions (Mitchell, 2001). Different variations of genetic algorithms have been applied to a large number of scientific and engineering problems. In this paper we use a genetic program named DARWIN (Álvarez et al., 2001) to model and predict the dynamics of the weekly exchange rates of the Japanese

Yen and on the Pound Sterling against the American Dollar. The evolutionary process developed by the genetic program can be explained by means of a series of stages. At a first stage, the genetic program creates a random initial population of N mathematical equations susceptible of representing accurately the time series evolution. These mathematical equations are created by means of a random combination of operators and arguments in the following way:

$$S_j : \ ((A \otimes B) \otimes (C \otimes D)) \quad \forall\, 1 \leq j \leq N \tag{2}$$

where A, B, C, and D are the arguments (operand genes), the symbol $\otimes$ represents the mathematical operators (operator genes) and the subscript *j* refers to each one of the N equations belonging to the initial population. Arguments can be real numbers included in a certain interval (the equation coefficients) or independent variables (delays of the variable). The mathematical operators ($\otimes$) used will be sum (+), subtraction (-), multiplication (·) and protected division (/) to prevent zero divisors. It is also possible to include other mathematical operators (such as logarithm or the trigonometric ones) but at the expense of increasing the complexity in the functional optimization process. Moreover, previous studies on genetic programming have demonstrated that it is possible to describe complex dynamics with mathematical expressions that are built simply with these four arithmetical operators (Szpiro, 1997; Yadavalli et al., 1999; Álvarez et al., 2001).

At a second stage, after specifying the initial population of candidates, the evolution process starts selecting those equations that fit best to the problem. Researchers usually measure fitness by some least-squares measures of goodness of fit. In our case, the

Theil's U statistic has been adopted as fitness criterion. This performance measure is widely applied in financial forecasting because it allows us to compare directly the prediction performance of the proposed method with the random walk model (Fernández-Rodríguez et al., 1999). Therefore, the U-Theil can be defined as:

$$U_j = \frac{\sqrt{\sum_{t=1}^{M} (e_t - \hat{e}_t)^2}}{\sqrt{\sum_{t=1}^{M} (e_t - e_{t-1})^2}} \qquad \forall \mathrm{j} = 1,\ldots,\mathrm{N} \tag{3}$$

where U_j is the U-Theil presented by the j-th equation ($\forall\ 1 \leq j \leq N$), e_t represents the observed time series, $\hat{e}_t$ is the predicted value and M is the total number of observations reserved to train the genetic program.

A roulette wheel selection method (Mitchell, 2001) was used to breed a new generation of equations. Those equations of the initial population whose U_j values are extremely high are automatically annihilated. The rest of the equations will have associated a probability of selection depending on their U-Theil values. In this way, those equations with low values are more likely to survive, and those equations with high values are more likely to be deleted.

After the selection process, the surviving equations are used to create the equations of a new solutions generation (i.e., reproduction process). In order to do that, the so-called genetic operators will be applied: cloning, crossover and mutation. With the cloning operator, the fittest equations are exactly replicated in the next generation. Using this elitist strategy, we avoid an involution in the optimization process due to a lost of information. With the crossover operator, pairs of equations with low values of U_j have more chances to be selected in order to exchange part of their arguments and of their mathematical operators. Finally, mutation means that any operator or argument is randomly replaced in a small number of equations. The first top ranked equations are exempted from mutation in order to avoid a possible lost of information (Beenstock and Szpiro, 2002). This elitist procedure in mutation guaranties that the candidate equations do not get trapped in a local optimum, converging prematurely to a stable but relatively low fitness.

In order to clarify the explanation, let us consider, for example, that the following equations belong to the initial population:

$S_1 : (A+B)/C$

$S_2 : (D \cdot E) - G$

where A, B, C, D, E and G are the equation arguments (coefficients and independent variables). Let us suppose that both expressions will survive the selection process and so they become the base equations for the next generation. The crossover operator means the random selection of a block of operators and arguments in each equation and their later exchange. For instance, let us suppose that the block (A+B) in expression S_1 and the argument G in expression S_2 have been selected. By means of an exchange of blocks two news equations appear as follows:

$S_3 : G/C$

$S_4 : (D \cdot E) - (A+B)$

As one can observe, the new equations inherit certain features from their parents. Now let us suppose that the expression S_1 is selected again and the mutation operator is applied. So, the following equation can be obtained from S_1:

$$S_5 : (A \cdot B) / C$$

where the mutation was the random alteration of a mathematical operator.

In short, the new population created from the initial population of equations is composed of cloned equations (such as S_2), mutated expressions (such as S_5), or crossed (such as S_3 and S_4). From this moment, the process will repeat the selection and reproduction stages in an iterative way. After a given number of generations, determined by the user, the iteration procedure ceases and an approximation to the true but unknown dynamics of the time series $F(\cdot)$ is given by the strongest mathematical equation in the population.

III-. Data and Forecasting /Strategy Simulation Setup

The database employed in this study was taken from the Pacific Exchange Rates Service (University of British Columbia), and it is composed of weekly exchange rates of Japanese Yen and British Pound against the American Dollar. Following a common practice in finance, the considered data is the exchange rate during a representative day of the week, usually Wednesday. If a particular Wednesday happens to be a non-trading day, then either Tuesday or Thursday are retained (Lo and MacKinlay, 1988, Diebold and Nason, 1990). The sample finally chosen runs from the first week of 1973 to the last week of July 2002, (comprising a total of 1542 observations). We consider that the choice of a weekly frequency is justified because it minimizes the bias which can exist in daily data, such as daily effect and week-end effect. Moreover, as Yao and Tan (2000) pointed out, weekly data are assumed to contain sufficient information to be able to accurately reflect the dynamics of exchange rates.

Usually, the majority of the research on exchange rates forecasting has used the difference of the exchange rate logarithm. Working in differences is presented in the literature as desirable and an extremely interesting variable for financial operators (Brooks, 1996). In spite of this recommendation and its generalized use, in our analysis we prefer to work in levels. Our justification lies on the fact that differencing can increase the existing noise in the time series and, therefore, destroy some deterministic and predictable signal (Broomhead and King, 1986; Peters, 1991; Soofi and Cao, 1999). Moreover, as Kaboudan (2000) has empirically confirmed using genetic programming, financial prices have a higher chance of being predicted than financial returns.

In order to find possible overfitting problems and to evaluate the predictive ability of the genetic program, the sample was divided into three sub-samples: training, selection and out-of-sample. The first one, composed by the first 1080 observations, was reserved exclusively for the evolution of the genetic programming. The selection period, which covers the 306 following observations, is employed to determine the optimum number of delays and to adjust certain aspect of the genetic program setup. Finally, the last 156 observations are reserved to validate the predictive power of the genetic program. Therefore, the out-of-sample set contains observations which were not used neither by the GP during the evolutionary process nor by the researcher to select technical parameters. It will be necessary that the fitting criterion achieved by the final surviving equation showed a similar and relatively high value in the training, selection and out-of-sample sets. If this condition was verified, it would be proved the ability of the surviving model to generalize new observations and, therefore, the no-existence of over-fitting problems.

The fitting criterion which we use to validate and judge the results is the U-Theil, defined by the expression (2). This criterion compares the errors obtained by the purposed forecasting method and the errors obtained by considering the previous value of the exchange rate as predictor. As such, a U-Theil value that is lower than/equal to/higher than one would imply a forecasting capability better than/equal to/worse than the random walk model. This criterion was quite employed in financial forecasting (Fernández-Rodríguez et al., 1997) and, specifically, in predicting exchange rate (Fernández-Rodríguez et al., 2004; Kaboudan, 2005).

Regarding the strategy simulation setup, we employ the predictions obtained by the genetic program to articulate a simple trading strategy, and we verify what it would have happened if we had invested one dollar (back-testing procedure). The back-testing period covers from 28/07/1999 to 31/07/2002 (out-of-sample period). Buying and selling orders are based on the following *if-statements*:

· If $\hat{e}_{t+1} - e_t < 0$ and $\left|\hat{e}_{t+1} - e_t\right| > c \cdot e_t$, then buy the currency

· If $\hat{e}_{t+1} - e_t > 0$ and $\left|\hat{e}_{t+1} - e_t\right| > c \cdot e_t$, then sell the currency where e_t is the exchange rates, $\hat{e}_{t+1}$ is the predicted value and c the transaction cost of trading currency. The transaction costs are assumed to be paid each time that a selling or buying order is made.

When constructing this simple strategy, we take into account both sign prediction and point prediction. From a practical point of view, it is considered more interesting to predict the direction of the sign than the exact value of the variable: the smallest forecast errors could cause heavy losses in capital if the direction of the forecast is mistaken (Tenti, 1996; Lisi and Medio, 1997). However, our simple strategy also incorporates point prediction because we consider that not only the direction of the change is important, but also the magnitude of the prediction (Goodman, 1979). A speculator can allow short periods with loses if he obtains occasionally bigger profits in the future. On the other hand, for simplicity, we assume in our back-testing procedure that the speculator is risk neutral. However, it must be admitted that the speculators when they obtain profits are risk-averse and, when they obtain looses, they usually are risk-seeking (Tversky, 1990). We also assume that our investment will be small enough to avoid substantial modifications of the market conditions (no reflexibility phenomenon).

Finally, in the forecasting exercise, the technical configuration of the genetic programming was similar to that explained in Álvarez et al. (2001). The maximum number of arguments and mathematical operator in each equation were 20. Each generation had a maximum population of 120 equations and, in each case, a maximum of 5000 generations were considered. The crossover and mutation rates have been 0.2 and 0.1, respectively. The adequacy of this setup is guaranteed by previous work

(Álvarez-Díaz and Álvarez, 2003; Álvarez-Díaz and Álvarez, 2005) and it was also confirmed afterwards by a sensitivity study.

IV-. Results

Considering one-period-ahead forecasts, Figure 1 shows the sensitivity of the genetic programming in the face of different delays, in terms of the U-Theil values obtained in the selection period. As we can observe, both series show a certain forecasting stability considering different delays. However, following the recommendation of Casdagli (1989), we have chosen the number of delays which provides the lowest U-Theil in the selection period.

Table 1 and Table 2 depict the number of delays, the solution equations and the forecasting results for one period ahead. The results obtained are very similar for both exchanges rates. This fact confirms the believe in exchange rates forecasting that there is little variation in results from one exchange rate to another when weekly data is used (Diebold and Nason, 1990). Some interesting comments can be mentioned analysing Tables 1 and 2. First of all, we can observe how the fit criterion does show a relatively high accuracy and how there exists a small divergence among the training, selection and out-of-sample periods. This characteristic reveals the absence of a possible lack of generalisation using GP. It seems that the method has discovered the general pattern existing in the data rather than memorizing some specific features of the individual observations (overfitting problem). Secondly, the structure of the optimal equations found by the genetic program shows a strong dependence regarding e_{t-1} plus a nonlinear component depending on the most recent past return $\left(e_{t-1}-e_{t-2}\right)$. Thirdly, the out-of-sample U-Theil is lower than one and very similar for the Yen/$ and BP/$

(0.9665 and 0.9684, respectively). Therefore, the genetic program obtains better forecasts than the random walk model for both currencies. In order to verify whether or not the out-of-sample accuracy is statistically significant, we have applied the test purposed by Diebold and Mariano (1994). Let $\hat{e}_{t+1}^{GP}$ and $\hat{e}_{t+1}^{RW}$ be the predicted exchange rate using the genetic program and the random walk model, respectively. Let $error_{t+1}^{GP} = e_{t+1} - e_{t+1}^{GP}$ and $error_{t+1}^{RW} = e_{t+1} - e_{t}$ be their associated forecasting errors, and $d_t = (error_{t+1}^{GP})^2 - (error_{t+1}^{RW})^2$ the quadratic loss differential. These authors show that, under the null hypothesis of equal forecasts ability between methods $\left(H_0 : E(d_{t+1}) = 0 \text{ or } \mathrm{E}\left[(\mathrm{error}_{t+1}^{\mathrm{GP}})^2\right] = \mathrm{E}\left[(\mathrm{error}_{t+1}^{\mathrm{RW}})^2\right]\right)$, the following statistic follows asymptotically a standard normal distribution

$$D - M \text{ Test} = \frac{\bar{d}}{\sqrt{\dfrac{2\pi\, \hat{f}_d(0)}{H}}} \tag{4}$$

where H is the out-of-sample size, $\hat{f}_d(0)$ is a consistent estimate of the spectral density of the loss differential at frequency zero corrected for serial correlation and

$$\bar{d} = \frac{\sum\left[(error_{t+1}^{GP})^2 - (error_{t+1}^{RW})^2\right]}{H} \tag{5}$$

is the sample mean loss differential. A positive and statistically significant D-M test would imply to reject the null hypothesis and, in consequence, we could assert that the GP provides statistically better predictions that the Random Walk model. Observing the D-M Test in Tables 1 for the Yen/$ exchange rate, we cannot reject the null hypothesis that the random walk is not a statistically significant worse predictor than the solution equation obtained by the GP. Nevertheless, for the British Pound/$ we can find that our method shows a significant predictive accuracy and, therefore, it would provide evidence against the hypothesis that this exchange rate does follow a random walk process.

Tables 1 and 2 also show the success ratio of correctly predicted appreciations and depreciations. This ratio is defined as

$$SR = \frac{\sum_{t=m+1}^{M} \theta[r_t \cdot \hat{r}_t > 0]}{H} \tag{6}$$

where SR is the ratio of correctly predicted signs (Success Ratio), $r_t = e_{t+1} - e_t$ is the observed return, $\hat{r}_t = \hat{e}_{t+1} - e_t$ is the predicted return, $\theta(\cdot)$ is the Heaviside function ($\theta(\cdot) = 1$ if $r_t \cdot \hat{r}_t > 0$ and $\theta(\cdot) = 0$ if $r_t \cdot \hat{r}_t < 0$), and, as before, H is the total number of observations in the out-of-sample period. The solution equations obtain an out-of-sample success ratio of 59.62 and 57.05 for the Yen/$ and BP/$, respectively. These percentages reflect the great difficulty in the literature to surpass the success ratio threshold of 60% (Lequarré, 1993), and they are according with previous research (Walzack, 2001). We apply the test proposed by Pesaran and Timmermann (1992) (P-T Test) to verify whether the percentages of successes obtained by the GP differ significantly from those that would have been achieved if the real returns (r_t) and the predicted returns ($\hat{r}_t$) were independent. To understand how this test works, let us consider $\hat{P}_e = \Pr(\hat{e} > 0)$, $P_e = \Pr(e > 0)$ and SR the success ratio previously calculated. The P-T Test adopt the following expression

$$P-T\ \text{Test} = \frac{SR - SR^*}{\sqrt{\hat{V}(SR) - \hat{V}(SR^*)}} \tag{7}$$

where SR^* is the ex-ante probability of correct sign prediction in the case that r_t and $\hat{r}_t$ were independent, $\hat{V}(SR)$ and $\hat{V}(SR^*)$ are the estimated variance for SR and SR^*, respectively. Formally,

$$SR^* = \Pr(r_t \cdot \hat{r}_t > 0) = P_e \cdot P_{\hat{e}} + (1 - P_e) \cdot (1 - P_{\hat{e}}) \tag{8}$$

$$\hat{V}(SR) = \frac{SR^* \cdot (1 - SR^*)}{H} \tag{9}$$

and

$$\hat{V}(SR^*) = \frac{1}{H^2} \cdot \left\{ \begin{array}{l} H \cdot (2 \cdot \hat{P}_e - 1)^2 \cdot \hat{P}_{\hat{e}} \cdot (1 - \hat{P}_{\hat{e}})^2 + H \cdot (2 \cdot \hat{P}_{\hat{e}} - 1)^2 \cdot \hat{P}_e \cdot (1 - \hat{P}_e) + \\ + 4 \cdot \hat{P}_e \cdot \hat{P}_{\hat{e}} \cdot (1 - \hat{P}_e) \cdot (1 - \hat{P}_{\hat{e}}) \end{array} \right\} \tag{10}$$

Under the null hypothesis of independence, Pesaran and Timmermann (1992) show that the P-T Test is asymptotically distributed as a standard normal. In our forecasting exercise, the results derived from the application of the test reflect that there certainly seem to be statistical arguments for rejecting the hypothesis of independence between the values of the exchange rates and the values predicted by the GP for both currencies. Therefore, we can assert that the sign prediction obtained by the GP differs significantly from the 50%, expected success ratio if the exchange rate returns were independent and unpredictable.

In Figure 2 we find out the possibility of nonlinear dependence for different forecasting periods. If the exchange rates followed a random walk process, we would expect that the k-steps-ahead forecasts wandered around a U-Theil value equal to one. However, for both exchange rates, we can observe how the most accurate predictions is achieved for one period ahead and, for more periods ahead, the out-of-sample U-Theil increases and fluctuates around one. Following the methodology developed by Sugihara and May (1990) and empirically applied in economics by Finkenstädt and Kuhbier (1995) and Agnon et al. (1999), this characteristic seems to corroborate the existence of a slightly short-term predictable pattern in the studied exchange rates.

Regarding the strategy simulation, we verify what there would have happened if we had employed the GP forecasts and the *if-statements* defined in the previous section, from 28/07/1999 to 24/7/2002. We assume that the initial amount of the investment is one US-Dollar, and we check what final amount we would have achieved at the end of the out-of-sample period. Table 3 and Table 4 detail a complete information about the transactions made for the Yen/$ and the BP/$, respectively. As we can observe, the tables provide information about when the buy and sell orders were made, at what price and the final profit for each transaction. Table 5 comprises and summarizes the trading strategy results. At the end of the back-testing period, the strategies based on GP predictions obtain positive profits for both currencies (12.19 and 9.23 Cents for the Yen/$ and the BP/$, respectively). In order to verify the statistical significance of these profits, we generate artificially 1.000 time series randomly shuffling the predictions obtained by the GP. By scrambling the predictions, any possible deterministic structure should be destroyed maintaining the distributional properties of the original series. Later on, we apply the *if-statements* using these artificial series, we calculate their corresponding profit and, finally, we construct an empirical distribution of profits. If there was no information in the GP predictions, the profit by the original series should not be statistically different than the profits obtained by the shuffled series. Using the empirical distribution of profits, we can build a confidence interval with a specific significant level, in our case at the 95 percent. Any profit inside the empirical interval would be considered as the result of the application of the *if-statements* based on random signals. As we can observe, the *if-statements* trading rules based on GP predictions obtain profits statistically different from random trading decisions. Therefore, we can affirm that extraordinary profits can be achieved in the Foreign Exchange Market using nonlinear forecasting methods and simple trading rules. In Table 5, the annual return rate calculated by the expression

$$\pi = \left(\frac{\mathit{Money}\ \text{Obtained}}{\text{Seed Money}} \right)^{\frac{52}{H}} - 1 \qquad (11)$$

is also showed (Yao and Tan, 2000). For the specific case of the Yen/$, the annual return rate is 3.88% and a little bit lower percentage for the BP/$, 3.01%. Additional information has been added as the number and percentage of positive transactions, and the Sharpe Ratio (RS). This ratio is composed by the ratio between the mean of the transaction profits and its standard deviation. Therefore, when comparing trading strategies, a higher RS implies higher mean return and/or lower volatility. In our empirical exercise, the RS for both currencies are very similar; even thought the RS for Yen/$ is slightly superior.

In spite of obtaining extraordinary profits, these results must not be considered definitive or conclusive because of the existence of transaction costs should be taken into account (LeBaron, 1993). Many researchers have erroneously omitted the presence of transaction costs in their analysis assuming that they were very low. Nevertheless, the presence of transaction costs can make a strategy unprofitable since requires frequent buying and selling orders. Following Levich and Thomas (1993) and Swingler (1996), and considering that the on-line financial-transactions commission charged is approximately 0.1%, we have assumed transaction costs of 0.1 and 0.5% in our analysis. As we can observe in table 5, when transaction costs are added, the extraordinary profits drastically disappear or they become negatives, and the annual return rates, number of transactions and RS fall. Therefore, it seems that thanks to the existence of transaction costs, the Efficiency Hypothesis is verified in the Foreign Exchange Market. The transaction costs would be small enough to interfere in the market, but they are big enough to be responsible for the efficiency of the market. This affirmation is in accordance with previous studies already published in the literature (Rawani et al., 1993; Satchell and Timmermann, 1996).

A final comment must be made in order to explain the positive and relatively high profit obtained for the BP/$ when a transaction cost of 0.5% is considered. In this specific case, only one buy order has been generated (27/09/2000) and no sell order. Therefore, at the end of the out-of-sample period (31/07/2002), the currency is sold and a positive profit is achieved.

V-. Conclusion

As mentioned in the introductory section, many authors have empirically demonstrated that foreign exchange rate markets are efficient. This statement implies that exchange rates are well approximated by a random walk model, their returns are unpredictable, independent and identically distributed and it is not possible to articulate profitable trading rules. In this paper we have employed a Genetic Program to predict the dynamic evolution of the Yen/$ and BP/$ exchange rates, and verify whether or not the method can beat the random walk model. Later on, we use the predicted values to generate a trading rule based on simple “if-statements” and we check the possibility of obtaining extraordinary profits.

Regarding the forecasting exercise, our results reveal a slight forecasting capability for one-period-ahead when point prediction is analysed, and statistically significant for the specific case of the BP/$. This is in agreement with previous results which show that certain non-linear prediction methods are slightly superior to the random-walk model in forecasting exchange rates one-period-ahead. For example, similar results have been obtained by Fernández-Rodríguez et al. (2002) employing nearest neighbour, Tenti (1996) using neural networks, Álvarez-Díaz and Álvarez (2005) considering data-fusion or, for the specific case of genetic programming, Álvarez-Díaz and Álvarez (2003). However, when more periods-ahead are considered, the slight forecasting capability is lost. This fact has been also previously verified by Diebold and Nason (1990). On the other hand, when sign prediction is analysed, the solution equations which survive to the evolutionary process statistically outperformed the random walk directional forecast, even thought the 60% forecasting threshold reported in the literature has not been exceeded.

In summary, our predictive analysis provides evidences against the unpredictability of the exchange rates evolution and, in consequence, against the belief that the exchange rates follow a random walk process. Considering both point prediction and sign prediction, GP offers statistically significant better predictions than the random walk model, except for the Yen/$ point prediction one-period-ahead.

Analysing the economic value of the prediction, our strategy based on simple "*if-statements*" allows obtaining positive profits which are statistically different from those which would be obtained under random decisions. However, when transaction costs are incorporated in the exercise, the profits practically disappear or become negative. Therefore, in spite of getting accuracy predictions and beating the random walk model, the existence of transaction costs guarantee the compliance of the market efficiency. We cannot achieve extraordinary profits using automatic trading strategies based on genetic programming predictions. However, this conclusion must be qualified. Future research on financial forecasting could allow even more accurate predictions and/or improve the economic results of the trading strategies. For example, as White (1996) has pointed out, it is possible that techniques capable of finding and exploiting hidden nonlinear structures have not yet been developed or applied. Another possible improvement consists in using explanatory variables based on technical analysis instead of delays (Franses and Griensven, 1998). Moreover, we should also take into account that we have employed a very simple "*if-statements*" to generate our trading strategy. Perhaps the incorporation of more "*if-statements*" from other forecasting methods (confirmation method) and/or increasing their complexity would allow obtaining a significant and positive profit when transaction costs are included in the analysis.

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Figure 1. Selection of the Embedding Dimension

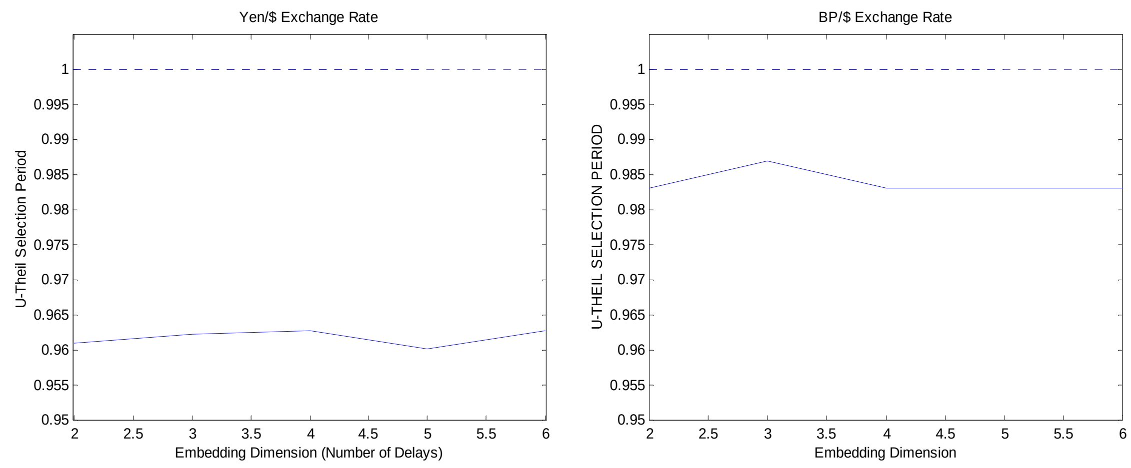

Figure 2. Point Prediction to Different Periods.

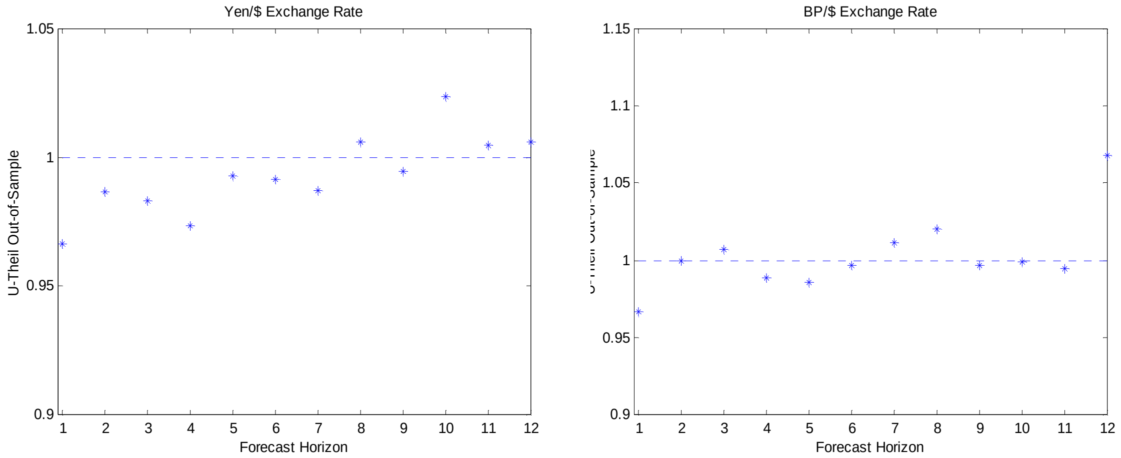

Table 1. Genetic Programming Forecasting Results for the Yen/$ Exchange Rate

<table>
<tr><th rowspan="3">Embedding Dimension</th><th colspan="4">Point Prediction</th><th colspan="4">Sign Prediction</th></tr>
<tr><th colspan="3">U-Theil</th><th rowspan="2">D-M Test (p-value)</th><th colspan="3">Success Ratio</th><th rowspan="2">P-T Test (p-value)</th></tr>
<tr><th>Training</th><th>Selection</th><th>Out-of-sample</th><th>Training</th><th>Selection</th><th>Out-of-sample</th></tr>
<tr><td>5</td><td>0.9549</td><td>0.9601</td><td>0.9665</td><td>1.4953
(0.1348)</td><td>61.67</td><td>59.8</td><td>59.62</td><td>2.36
(0.0091)</td></tr>
<tr><td colspan="9">Equation</td></tr>
<tr><td colspan="9">$$\hat{e}_t = e_{t-1} + \frac{0.326 \cdot \left(e_{t-1} - e_{t-2}\right) \cdot e_{t-1}}{e_{t-5}}$$</td></tr>
</table>

Table 2. Genetic Programming Forecasting Results for the BP/$ Exchange Rate

Embedding Dimension	Point Prediction				Sign Prediction			
	U-Theil			D-M Test (p-value)	Success Ratio			P-T Test (p-value)
	Training	Selection	Out-of-sample		Training	Selection	Out-of-sample	
2	0.958	0.983	0.9684	**1.8987** (0.0576)	61.94	56.54	57.05	1.7672 (0.0386)
Equation								
$\hat{e}_t = e_{t-1} + \dfrac{0.66 \cdot \left(e_{t-1} - e_{t-2}\right)}{7.19 - 7.65 \cdot e_{t-2}^2}$								

Table 3. Trading Strategy Results for the BP/$ Exchange Rate

Transaction	BUY ORDER		SELL ORDER		Profit (¢)	Transaction	BUY ORDER		SELL ORDER		Profit (¢)	Transaction	BUY ORDER		SELL ORDER		Profit (¢)	Transaction	BUY ORDER		SELL ORDER		Profit (¢)
	Date	Price (¥/$)	Date	Price (¥/$)			Date	Price (¥/$)	Date	Price (¥/$)			Date	Price (¥/$)	Date	Price (¥/$)			Date	Price (¥/$)	Date	Price (¥/$)	
1	04/08/99	114,5	11/08/99	115,2	-0.65	**10**	17/05/00	108,9	31/05/00	107,6	1.16	**19**	21/02/01	116,1	28/02/01	117,3	-0.95	**28**	13/02/02	133	20/02/02	133,6	-0.48
2	18/08/99	112,76	29/09/99	106,2	6.21	**11**	07/06/00	106,2	14/06/00	106,6	-0.37	**20**	11/04/01	124,4	09/05/01	122	1.91	**29**	06/03/02	130,1	20/03/02	132	-1.40
3	13/10/99	106,5	03/11/99	104,8	1.59	**12**	21/06/00	105,1	28/06/00	105,6	-0.44	**21**	23/05/01	121	06/06/01	120	0.72	**30**	03/04/02	132,7	08/05/02	128	3.66
4	24/11/99	104,04	08/12/99	102,7	1.32	**13**	02/08/00	109	16/08/00	108,8	0.15	**22**	11/07/01	124,8	01/08/01	124,4	0.27	**31**	15/05/02	127,7	12/06/02	125	2.09
5	22/12/99	102,19	05/01/00	104,3	-2.02	**14**	23/08/00	107,6	13/09/00	106,9	0.62	**23**	08/08/01	123	05/09/01	120,3	2.27						
6	19/01/00	105,23	26/01/00	105,9	-0.60	**15**	11/10/00	107,7	18/10/00	108,4	-0.63	**24**	12/09/01	119,2	26/09/01	118,4	0.69						
7	01/03/00	108,24	22/03/00	107	1.18	**16**	25/10/00	108,3	01/11/00	108,5	-0.15	**25**	31/10/01	122	14/11/2001	122	-0.02						
8	29/03/00	105,36	12/04/00	106	-0.60	**17**	08/11/00	107,5	15/11/00	108,7	-1.11	**26**	16/01/02	131,9	23/01/2002	134	-1.55						
9	19/04/00	104,79	26/04/00	106,4	-1.54	**18**	24/01/01	117,1	07/02/01	115,9	1.03	**27**	30/01/02	133,5	06/02/2002	133,7	-0.17						

Table 4. Trading Strategy Results for the BP/$ Exchange Rate

Transaction	BUY ORDER		SELL ORDER		Profit (¢)
	Date	Price (¥/$)	Date	Price (¥/$)	
1	1/9/99	0.624	15/9/99	0.619	0.814
2	22/9/99	0.612	27/10/99	0.606	0.919
3	17/11/99	0.618	24/11/99	0.619	-0.28
4	8/12/99	0.616	15/12/99	0.620	-0.67
5	29/12/99	0.62	26/01/00	0.61	1.52
6	23/2/00	0.624	01/03/00	0.631	-1.18
7	22/3/00	0.634	12/04/00	0.630	0.584
8	31/5/00	0.668	14/06/00	0.662	0.98
9	28/6/00	0.663	12/07/00	0.663	-0.11

Transaction	BUY ORDER		SELL ORDER		Profit (¢)
	Date	Price (¥/$)	Date	Price (¥/$)	
10	26/7/00	0.661	02/08/00	0.668	-0.975
11	9/8/00	0.666	16/08/00	0.667	-0.096
12	20/9/00	0.704	04/10/00	0.687	2.3891
13	11/10/00	0.685	18/10/00	0.692	-1.09
14	1/11/00	0.69	08/11/00	0.700	-1.41
15	29/11/00	0.703	10/01/01	0.671	4.8078
16	31/1/01	0.682	07/02/01	0.686	-0.501
17	28/2/01	0.689	14/03/01	0.691	-0.25
18	28/3/01	0.699	18/04/01	0.697	0.3529

Transaction	BUY ORDER		SELL ORDER		PR. (¢)
	Date	Price (¥/$)	Date	Price (¥/$)	
19	25/4/01	0.695	02/5/01	0.697	-0.298
20	16/5/01	0.701	23/5/01	0.704	-0.436
21	20/6/01	0.711	4/7/01	0.711	0.003
22	11/7/01	0.710	8/8/01	0.704	0.906
23	15/8/01	0.696	19/9/01	0.683	1.972
24	26/9/01	0.680	10/10/01	0.689	-1.272
25	31/10/01	0.686	14/11/01	0.696	-1.43
26	28/11/01	0.704	26/12/01	0.691	1.917
27	06/02/02	0.706	20/2/02	0.700	0.925

Transaction	BUY ORDER		SELL ORDER		Profit (¢)
	Date	Price (¥/$)	Date	Price (¥/$)	
28	6/3/02	0.702	13/3/02	0.7045	-0.2825
29	20/3/02	0.701	27/3/02	0.7017	-0.024
30	3/4/02	0.696	10/4/02	0.6966	-0.066
31	17/4/02	0.692	8/5/02	0.6842	1.2775
32	22/5/02	0.686	5/6/02	0.6846	0.241

Table 5. Summary Trading Strategy Results

	NO TRANSACTION COSTS					TRANSACTION COSTS							
						0.1%				0.5%			
	Profit (Cent. $)	**Empirical Confidence Interval (95%)**	**Annual Profit rate**	**Number Trans.**	**RS**	**Profit (Cent. $)**	**Annual Profit rate**	**Number Trans.**	**RS**	**Profit (Cent. $)**	**Annual Profit rate**	**Number Trans.**	**RS**
YEN/$	12.19	(-9.23, 11.72)	3.9%	31	02337	2.82	0.94%	26	0.0587	0.9114	0.3%	5	0.0434
BP/$	9.23	(-11.65, 8.21)	3.0%	32	0.221	-3.6	-1.22%	14	-0.1440	6.89	2.2%	1	-