Detecting and exploiting trends in the foreign exchange markets

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Abstract

This paper is devoted to testing for the random walk hypothesis against the existence of trends in exchange rate series for 95 currencies against the US Dollar. To that end, we make use of Taylor's price trend model (Taylor, S., 1980) that, instead of focusing on the mean reverting behaviour of exchange rates measured over a long horizon, concentrates on the short-term pattern of the price trend. A maximum likelihood method is used to estimate the model parameters using a genetic algorithm. Optimal one-step-ahead forecasts of returns are derived and trading rules based on these forecasts are constructed. These trading rules, that bear similarity to the popular trading rules based on moving averages, overcome the buy-and-hold strategy in 25 out of 39 cases where trends are detected, even in the presence of transaction costs.

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1. Introduction

The efficient market hypothesis (EMH) is a theme long discussed in financial literature. In its weak form, the EMH establishes that current prices reflect all available public information in the past and investors are only compensated by taking risks. It means that the new information arriving on the market is instantaneously translated to prices and employing any technical trading strategy it is impossible to obtain an abnormal profit above the market, because the weak form of the EMH implies that the market price follows a random walk model. Thus, for the EMH view the underlying economic fundamental are the best way for making trading decisions.

In an alternative way, the defenders of technical analysis maintain that prices move following trends. So, when new information arrives at the market it does not immediately translate into prices and a certain amount of time is necessary until the market incorporates the information. This situation will reflect that the market will move through trends which may be used in a profitable way using a technical trading strategy based on the correlations of past returns.

There was a seminal paper by Taylor (1980) casting doubt over the random walk hypothesis and introducing a price trend model which provided profitable rules in commodity and currency markets. Until the end of the eighties, the literature defended the EMH which supports that no technical trading rule may be able to make extra profits over the naïve buy and hold strategy, taking into account transaction costs.

After the 1987 market crash, a number of researches have begun to examine the role of non-fundamental analysis in financial markets. Some of them have suggested that technical analysis may have been an important contributory factor in the 1987 crash (see Shiller, 1989, among others). In a similar fashion, in the exchange rate markets it was also brought into question the hypothesis that market practitioners utilize rational and efficient information in forming their expectations. In this sense, Frankel and Froot (1986, 1990) blame technical analysis for the overvaluation of the US dollar during the 1980s, mean while the economic fundamentals pressured in opposite direction. Therefore, the academic studies begun to recognise the role the "noisy traders" in financial markets: traders who do not use or who misperceive the fundamentals.

This initial scepticism of the EMH gave rise to other empirical studies which begun to reveal that there are numerous anomalies and situations in the financial markets where future returns are predictable from past returns. So, Lo and MacKinlay (1988) found positive autocorrelations of weekly returns on portfolios of NYSE stocks. Fama and French (1988) discovered negative serial correlation in returns of individual stocks and various portfolios of small and large firms. Brock, Lakonishok and LeBaron (1992) reported that most common technical trading rules as moving average and trading rank break have predictive power in the Dow Jones index. Similar conclusions have been reached by Gencay (1996), who found strong evidence of nonlinear predictability in daily returns of the Dow Jones index, and Kwan *et al.* (2000), who found predictability and profitability considering the price trend model by Taylor (1980) in the Hang Seng Index Futures in Hong Kong Finally, Szakmary *et al.* (2010) offer empirical evidence supporting the performance of trend-following trading strategies in commodity futures markets.

For the foreign exchange markets there are also a wide empirical evidence of the success of technical trading strategies. Numerous authors support that, even after taking into account interest rate differentials and transaction costs, standard moving average rules yield excess profits for the most US-dollar exchange rates. Besides, using artificial data instead of actual foreign exchange data, this profitability is statistically significant. In this sense, see Dooley and Shafer (1983), Sweeney (1986), Levich and Thomas (1993), LeBaron (1998), Gencay (1999), Neely et al (1997), Chang and Osler (1999), Dewachter (2001) and Harris and Yilmaz (2009), among others. So, all this empirical evidence in favour of trend follower technical trading rules cast doubts with respect to the efficiency of the exchange rate market and about the random walk as an appropriate model for explaining its returns.

The purpose of this paper is to re-examine the random walk hypothesis for exchange rates of ninety-five countries using daily data from 4 January 1993 to 8 August 2008. In doing so, our study provides interesting information from a wide sample of countries with different exchange-rate regimes, and will complement existing studies on developed markets. In addition, we offer further evidence on the ability for generating profitable trading rules using price-trend models, even when transaction costs are taking into account. Finally, we propose the use of genetic algorithms in the econometric methodology to boost the optimization technique.

The paper is organised as follows. Section 2 presents the econometric methodology used for testing for the random walk hypothesis against the existence of trends in financial time series. Section 3 describes the data set and reports our empirical results. In Section 4, we assess the economic value of technical trading strategies based on the trend model. Finally, Section 5 provides some concluding remarks.

2. Econometric methodology

Following the weak EMH, the random walk model represents the movement of financial market asset returns

$$\begin{aligned} &x_t = \log(P_t) - \log(P_{t-1}) = \mu + \varepsilon_t, \\ &E(\varepsilon_t) = E(\varepsilon_t \varepsilon_{t+i}) = 0 \quad i \neq 0 \end{aligned} \tag{1}$$

where P_t is the price of an asset in the instant t, μ is the expected change of the process, called the drift of the process, and the increments of daily returns $\{\varepsilon_t\}$ are IID with zero average.

In a seminal paper, Taylor (1980) introduces a trend model allowing μ to be variable with time being so a factor causing trends in prices, developing a statistical hypothesis framework to test whether the random walk models faithfully reflect the data generating process of the financial asset prices or, on the contrary, whether the prices have trends.

The trend model for a prices time series P_t is defined as

$$\begin{aligned} &x_t = \log(P_t) - \log(P_{t-1}) = \mu_t + \varepsilon_t, \\ &E(\varepsilon_t) = E(\varepsilon_t \varepsilon_{t+i}) = 0, \ i \neq 0, \operatorname{cov}(\mu_s, \varepsilon_t) = 0 \quad \forall s, t \end{aligned} \tag{2}$$

where the drifts μ_t are uncorrelated with white noise series ε_t. In this case, μ_t is a stochastic process representing the trend in the model and it is interpreted as the answer to anticipated changes in the supply and demand of the assets. This μ_t may be positive or negative giving rise to increasing or decreasing price trends

In what follows we call σ^2 to the variance of ε_t, v^2 to the variance of μ_t and $\bar{\mu}$ to the expectation of μ_t.

The trend models rests in five basic assumptions:

1) The trend values are determined by the actual information of supply and demand arriving on the market.
2) The new information arrives randomly on the market.
3) There is new information in the proportion of $1-p$ trading days, where $0 \leq p \leq 1$.
4) The trend values change only when the new information arriving on the market is available.
5) When the trend values change, the new value is independent of all past values.

These assumptions are consistent with the gradual information diffusion hypothesis of Hong and Stein (1999). In their model, financial market is populated by two groups of boundedly rational agents: "news-watchers" (trading on fundamental information) and "momentum traders" (trading on past price movements). If information diffuses gradually across the population, prices underreact in the short run, therefore allowing the momentum traders to profit by trend-chasing. Furthermore, Friesen *et al.* (2009) present an alternative momentum explanation to the gradual information diffusion hypothesis assuming that decisions are affected by a psychological bias affecting future price changes and allowing that certain trading strategies based on past prices can be profitable.

So, the trend model may be formulated with probability as

$$\mu_t = \begin{cases} \mu_{t-1} & \text{with probability} \quad p \\ \bar{\mu} + \eta_t & \text{with probability} \quad 1-p \end{cases} \tag{3}$$

where η_t is a white noise with mean zero and independent of the past trend values μ_s for $s < t$.

In order to find out the number of days that the duration of the trend is expected, it is defined a parameter *m* which is called the mean trend duration. This parameter averages the different durations of possible trends

$$m = \sum_{i=1}^{\infty} i(1-p)p^{i-1} = (1-p)^{-1} \tag{4}$$

For instance, if *m* were equal to 5 days, we can say that, on average, the asset would move with the same trend μ_i, positive or negative, for 5 days until new information arrived to the market and the trend changed in μ_{i+6}.

The aforementioned trend model is not very realist because it is very well known that the variance of daily returns is time changing, that is, $\mathrm{var}(x_t) = \Sigma_t^2$.

Furthermore, it is reasonable to assume that both $\mathrm{var}(\varepsilon_t)$ and $\mathrm{var}(\mu_t)$ are time depending quantities. So, as a time varying variance causes serious problems in obtaining the sample correlations, Taylor and Kingsman (1979), Taylor (1980) and Taylor (2008) developed a new methodology with the end of dealing with time varying variance. In this methodology it is necessary to introduce the additional assumption that the ratio $R = \mathrm{var}(\mu_t)/\mathrm{var}(\varepsilon_t)$ in (2) is roughly constant in the time. So, Taylor rescales the trend values in the way μ_t / Σ_t. In this case, denoting the average $E(\mu_t / \Sigma_t)$ as $\bar{\mu}$, we have a trend model with fluctuating variance,

$$\mu_t = \begin{cases} (\Sigma_t / \Sigma_{t-1})\mu_{t-1} & \text{with probability } p \\ \bar{\mu}\Sigma_t + \eta_t \Sigma_t & \text{with probability } 1-p \end{cases}, \tag{5}$$

From equation (5) it follows that the variance of daily returns are roughly constant, which facilitates the empirical implementation of the statistical tests.

In order to estimate Σ_t and given that its relation with the mean absolute deviation a_t is $a_t = E|X_t| = \Sigma_t$ multiplied by a constant, Taylor prefers to estimate a_t rather than Σ_t. Therefore, a_t is estimated using an exponential weighted moving average of the past absolute price changes:

$$\hat{a}_t = \gamma \sum_{i=0}^{\infty} (1-\gamma)^i \,|\, x_{t-1-i} \,| = (1-\gamma)\hat{a}_{t-1} + \gamma \,|\, x_{t-1} \,|, \tag{6}$$

concluding that the parameter γ, obtained by the maximum likelihood method, is equal to 0.04 for stock prices and indexes and 0.1 for the remainder series (exchange rates, commodities, etc.).

The base of the price trend test is the existence of positive correlations between daily returns with several lags. On the contrary, in the random walk model, all correlations will be zero for any lag. For technical reasons the correlation employed in the test are the correlations between the rescaled returns $x_t / \hat{a}_t$ from (6).

The correlations of daily rescaled returns are defined as $\rho_i = cor(x_t / \hat{a}_t, x_{t+1} / \hat{a}_{t+1})$. For the model (1) of random walk the autocorrelations are zero for all lags. On the contrary Taylor shows that the model (2), (3) and (5) of series trends provides the following correlation expression

$$\rho_i = \frac{p^i v^2}{v^2 + \sigma^2} = Ap^i, \tag{7}$$

where $A = v^2 / (v^2 + \sigma^2)$.

So Taylor (1980) formulates a hypothesis test where the null corresponds to the random walk:

$$H_0 : \rho_i = 0, \text{ for each } i>0 \tag{8}$$

while the alternative hypothesis to random walk model is:

$$H_1 : \rho_i = Ap^i, \text{ for some } A \geq 0,\ 0 \leq p \leq 1, \text{ for each } i>0 \quad (9)$$

There are two parameters H_1: parameter A measures the proportion of information not instantaneously reflected by prices and parameter p measures the speed at which the imperfectly reflected information is incorporated into prices. If both A and p were very close to zero, the information would be used perfectly by the market. But when the trend is accepted, A has a small value, around 3%, and p is close to 1. It means that the market has a slow interpretation of the relevant information that arrives. The additional hypothesis that the ratio $R = \mathrm{var}(\mu_t)/\mathrm{var}(\varepsilon_t)$ in (2) is almost constant is necessary in order to permit a fluctuating variance in the model. As aforementioned, in this case, the time varying problems are avoided using rescaled returns $y_t = x_t / \hat{a}_t$, where $\hat{a}_t$ is defined in (6). This y_t has a variance approximately constant.

Although the trend model is nonlinear by nature, its autocorrelations resemble to the *ARMA(1,1)* model

$$x_t - px_{t-1} = \xi_t - q\xi_{t-1}, \quad \xi_t \approx IID(0, \sigma_\xi^2) \quad (10)$$

because its autocorrelations has also the form $\rho_i = Ap^i$ when *q* verifies the equation

$$q^2 - q\left\{\frac{1+(1-2A)p^2}{(1-A)p}\right\} + 1 = 0 \ \ for \ \ 0 \leq q \leq 1 \quad (11)$$

Therefore, as far as the autocorrelation functions are concerned, there exists a one to one correspondence between the class of price trend models and the *ARMA(1,1)* verifying (11). This does not mean that the two models are equivalent because their fourth or higher-order moments are different in general. Nevertheless, this correspondence may be used for forecasting purposes and forecasts of the future returns are generated under the price trend model by using the forecasts under the corresponding *ARMA(1,1)* model.

As Taylor (1980) observed, the previous tests employed in literature in order to refuse trends in time series are badly specified. The standard test used is the *Q*-test by Box-Pierce. This statistic doesn't offer any specific form to the alternative hypothesis. It has two serious shortcomings when prices have a trend as in (2) and (3). On the one hand, *Q* doesn't distinguish between positive and negative values of ρ_i, meanwhile Taylor's H_1 says that all ρ_i are positives. On the other hand, *Q* emphasis in the same way each one of the *k* first autocorrelation; on the contrary, in Taylor's H_1 a decreasing values of autocorrelations are expected.

In order to reject the presence of trends in the financial series Taylor (1980) proposes a statistic *T* based on the likelihood ratio, using the sample autocorrelations of rescaled returns $(r_1, r_2, ..., r_k)$ in (10).

$$T_{k,\phi} = \sum_{i=1}^{k} \phi^i r_i, \quad (0 < \phi < 1) \tag{12}$$

If H_0 is accepted, the statistic $T_{k,\phi}$ has *N(0,1)* asymptotic distribution. This statistic has only one tail, for which we reject the null hypothesis of random walk in favour of a trend with a significance level of 5% when T^* is higher than the critical value of 1.65. $T_{k,\phi}$ has the inconvenience that is not very robust in facing data errors in the price series. The first effect of a data error is the reducing of the first autocorrelation coefficient r_1 for which Taylor designed another statistic $U_{k,\phi}$ ignoring r_1:

$$U_{k,\phi} = \sum_{i=2}^{k} \phi^i r_i \ , (0 < \phi < 1) \tag{13}$$

$U_{k,\phi}$ is also normally *N(0,1)* asymptotically distributed. For both statistics it is necessary to choose *k*, ϕ and the significance level α. Taylor (1980) recommends using as better values *k = 30* and ϕ *= 0.92*. When H_0 is true the statistical U^* is

$$U^* = \frac{\sum_{i=2}^{30} 0.92^i r_i}{\sum_{i=2}^{30} (0.92^{2i} n^{-1})^{\frac{1}{2}}} = 0.4649\sqrt{n}\sum_{i=2}^{30} 0.92^i r_i \tag{14}$$

Once the trends were detected by the U^* statistic, the trend parameters *A, p, q* and *m* are going to be estimated in all series. As the parameter $A = v^2 / (v^2 + \sigma^2)$, it is necessary to estimate the variances v^2 and σ^2 in (2).

In order to estimate the trend parameters it is possible to use several methods. So Taylor (1980) employed the generalized method of moments. On the other hand Kwan *et al.* (2000) used the quasi-maximum likelihood in order to estimate the trend parameters in daily returns for Hang Seng Index Futures.

In this paper we will employ the maximum likelihood method in estimating the trend parameters. Following Taylor we try to match the theoretical Ap^i and the observed r_i autocorrelations, assuming the differences between them is $N(0,\sigma_r^2)$, that is

$$\begin{aligned} &r_i = Ap^i + \varepsilon_i \,,\ \varepsilon_i \approx N(0,\sigma_i^2)\,,\ i = 1,\ldots,n_r \\ &E(r_i) = Ap^i,\ \mathrm{var}(r_i) = \sigma_i^2\,, \end{aligned} \qquad (15)$$

where n_r is the number of simple autocorrelations r_i and σ_i^2 is the variance of the sample autocorrelations which following Barlett (1946) is given by the expression

$$Var(r_i) = \sigma_i^2 \approx \frac{1}{n}\left(1 + 2\sum_{k=1}^{i-1} r_k^2\right)$$

and *n* is the sample size of the training period.

In carrying out estimations, 200 sample autocorrelations of the rescaled returns are employed. Assuming that the residues $\varepsilon_i = r_i - Ap^i$ are independent, the likelihood function of the n_r residuals are

$$L(A, p / r_1, r_2, ..., r_{n_r}) = \prod_{i=1}^{n_r} \frac{e^{-\frac{1}{2\sigma_i^2}(r_i - Ap^i)^2}}{\sqrt{2\pi\sigma_i^2}} = \frac{e^{-\frac{1}{2\sigma_i^2}\sum_{i=1}^{n_r}(r_i - Ap^i)^2}}{(2\pi\sigma_i^2)^{n_r/2}} \tag{16}$$

Due to the complexity of function (16), in order to estimate the parameters A and p by maximizing the likelihood function, a genetic algorithm is employed.

A genetic algorithm (GA, hereafter) is a class of optimization technique, based on principles of natural evolution developed by Holland (1975) which try to overcome problems of traditional optimization algorithms, such as an absence of continuity or differentiability of the loss function. A GA starts with a population of randomly generated solution candidates, which apply the principle of fitness to produce better approximations to optimal solution. Promising solutions, as represented by relatively better performing solutions, are selected and breeding them together through a process of binary recombination referred to as crossover inspired by Mendel's natural genetics. The objective of this process is to generate successive populations solutions that are better fitted to the optimization problem than the solutions from which they were created. Finally, random mutations are introduced in order to avoid local optima [see Dorsey and Mayer (1995) for the use of genetic algorithms for optimizing complex likelihood functions in econometrics. Also see Haupt and Haupt (2004) as a simple introduction to genetic algorithms].

3. Data and empirical results

In this paper the study of the existence of trends is carried out using daily data of nominal exchange rates against the US dollar for 95 countries from 4 January 1993 to 8 August 2008[1] taking from Reuters´ EcoWin Pro.

In order to evaluate the capability of Taylor's price-trend model to exploit slight dependence among returns, it is necessary to subdivide each series into two parts: a training period and a prediction period. The training period is the first part of the time series and, inside it, the parameters *A*, *p* and *q* are estimated. These parameters will be employed for trading in the predicting period which is the second part of the series. The training period used to test for random walk hypothesis against trend ranks from the beginning of the series recorded by EcoWin Pro until 31-12-2007. The prediction period ranks from 01-01-2007 until 27-09-2008. For the series where the trend is accepted the characteristic parameters of the trend model are estimated. Finally, in the series where the mean trend duration is longer than two days, predictions are carried out in the prediction period.

Given that the countries in our sample present different exchange rate regimes that could affect the existence of trends, we have use the "natural fine classification" of Reinhart and Rogoff (2004), updated until December 2007 by Ilzetzki, Reinhart and Rogoff (2008), to distinguish between a wide range of *de facto* regimes:

1. No separate legal tender
2. Pre announced peg or currency board arrangement

[1] This period differs between series depending on data availability.

3. Pre announced horizontal band that is narrower than or equal to +/-2%
4. De facto peg
5. Pre announced crawling peg
6. Pre announced crawling band that is narrower than or equal to +/-2%
7. De factor crawling peg
8. De facto crawling band that is narrower than or equal to +/-2%
9. Pre announced crawling band that is wider than or equal to +/-2%
10. De facto crawling band that is narrower than or equal to +/-5%
11. Moving band that is narrower than or equal to +/-2% (i.e., allows for both appreciation and depreciation over time)
12. Managed floating
13. Freely floating
14. Freely falling
15. Dual market in which parallel market data is missing.

As the tables by Reinhart and Rogoff (2004) provide monthly data, we can not know the exact date of the change of regime. Therefore, we assume the regime change take place in the last day of the month.

Given that there are changes in the exchange rate regime in the 95 currencies examined in this paper, Table 1 provides an overview of the evolution of the statistical U* within each regime for each currency. This table reports for each individual currency and exchange rate regime, if at any time within that combination the statistic U* accepts the trend or not. To that end, we use the following codes:

0: the currency is not under a given exchange-rate regime

-1: the currency is under a given exchange-rate regime, but there is not evidence of the presence of a trend

+1: the currency is under a given exchange-rate regime and there is evidence of the presence of a trend at some point.

[Table 1, here]

For example, for the Australian Dollar we observe that it was never under regime 1 (no separate legal tender); it was under regime 2 (pre announced peg or currency board arrangement) in some subperiods, but we could not accept the presence of a trend; and it was under regime 8 (*de facto* crawling band that is narrower than or equal to +/-2%) in some subperiods and we find evidence of a trend.

As can be seen, we find evidence of the presence of a trend in the exchange rate in 93 cases. As one could have expected, these episodes are more frequent the more flexible the exchange-rate is (Figure 1). In addition, we find that the existence of a trend is generally accepted most frequently for currencies of developed countries and less frequently for currencies of developing countries. A reason for this finding could be that the latter have more efficient markets or because the former are more likely to have less flexible exchange-rate regimes.

[Figure 1, here]

Additionally, we repeated the study using all the available data, therefore ending in 27 September 2008. Given the absence of information in Reinhart and Rogoff about the exchange-rate regimen in 2008, we assume that the countries maintain the same exchange-rate that was previously effective. The results for this experiment are presented in Table 2. As it can be observed, several countries that did not accept the trend with data until December 2007 for their last known exchange rate regime, do accept the trend if we extend the sample until 27 September 2008. It is interesting to note that among these countries we find the Euro area and the United Kingdom.

[Table 2, here]

Table 3 reports the results of the U^* test as well as other important parameters in the trend model as it is the probability *p* of maintaining the trend, the parameter *A* of the correlation function in (7) and the mean trend duration obtained for the last known regime for each currency. As mentioned, all parameters were obtained by maximum likelihood employing a GA in the optimization process.

[Table 3, here]

As a general comment, it is possible to observe in Table 3 that the series where the statistic U^* accepts the trend predominate values of *A* which are lower than the values corresponding to the series where U^* accepts the null of random walk. The parameter *p* is usually higher than 0.5 in the series where the trend is accepted, which means that the new information needs more than one day to be incorporated into the prices. Note that for the series where the trend is not accepted we have not estimated the parameters *A*, *p*, *q* and *m*, so we have filled with zeros the corresponding columns.

With respect to U^* statistic, the results shown in Table 3 point out the following conclusions:

- In 56 out of a total of 95 exchange rates cases, the U^* statistic accepts the null hypothesis of random walk ($U^* < 1.65$, in a one-tail N(0,1) test with 5% of confidence)
- Trends are detected in 39 out of 95 exchange rates ($U^* > 1.65$), being trends more frequent in intermediate exchange-rate regimes (Figure 2).
- The mean trend duration is always higher than one day ($m>1$) when a trend is detected.

[Figure 2, here]

5. Economic evaluation of trends

Once the parameters associated with the trend model have been estimated, it is possible to construct technical trading strategies in order to beat the market. We will employ the strategy developed by (Taylor, 2008) aimed to profit from substantial trends in either direction. This strategy is compounded by three control parameters k_1, k_2 and k_t where $k_1 > k_2$. The parameter k_1 controls the commencement of trades, telling us when to change a short position for a long position. The parameter k_2 controls the conclusion of the trades, telling us when to change a long position for a short position.

Trading decisions depend on a standardized forecast k_t calculated by assuming the trend model, that is

$$k_t = \frac{f_{t-1,1}}{\hat{\sigma}_{F,t-1}} \tag{17}$$

where

$$f_{t-1,1} = (\hat{a}_t / \hat{a}_{t-1})\left\{(p-q)x_{t-1} + qf_{t-2,1}\right\} \tag{18}$$

$$\hat{\sigma}_{F,t-1} = \hat{a}_t \left\{Ap(p-q)/(1-pq)\right\}^{1/2} \tag{19}$$

with $t = 21,...,n_{rend}$, being n_{rend}, the total number of returns. In the recursion (18), $f_{t,1}$ is the *ARMA(1,1)* prediction made in the instant *t* of the return *t+1*, $\hat{\sigma}_{F,t}$ is its standard deviation, x_t is the no rescaled return of the series in the instant *t* and $\hat{a}_t$ is the estimated mean absolute deviation obtained in (6) with $\gamma = 0.1$ for exchange rate series and $\gamma = 0.04$ for stock prices and indexes.

The Taylor strategy is as follows: we need 20 returns before the beginning in order to estimate the mean absolute deviations ($\hat{a}_t$). The values of $f_{t,1}$ and $\sigma_{F,t}$ are assumed to be zero for $t \leq 20$, and for $t \geq 21$ are estimated recurrently in (18) and (19). After $t \geq 21$, we begin with no market position until $k_t > k_1$ (start a long position) or $k_t < k_2$ (start a short position).

When we are inside the market, if we are in a long position we change to a short position when $k_t < k_2$; if we are in a short position we change to a long position when $k_t > k_1$. For $k_t \in [k_1, k_2]$ don't change the position in any case. When we change our position from long to short or vice versa, a transaction cost of 0.05% is subtracted from the total return. Besides, in order to compute total returns, we assume that, when we are in a short position, the proceeds are invested in a money market account with a risk-free rate of 4% per annum (a year of 252 days is assumed).

In order to select the control parameters k_1 and k_2 an optimization process is carried out. So, k_1 and k_2 are selected, maximizing the Sharpe ratio of the Taylor strategy in the training period. With that end a GA is also employed.

Once the control parameters are estimated they are employed, together with the trend parameters (*A*, *p* y *q*) obtained in the training period, in the prediction period. The net return obtained in the period *t* to the series *i* is the following

$$R_i^t = \sum_{t=21}^{N_{rend}} (x_t\, buy_t) + \sum_{t=21}^{N_{rend}} \left[\left(x_t - riskf_i \right) sell_t \right] - c_i mov_t \tag{20}$$

where x_t is the no rescaled return, buy_t stands for a buy signal in the instant *t* (equal to 1 when we are in a long position and equal to 0 when we are in a short position or we take no market position), c_i is the transaction cost (0.05%), mov_t is the number of times that we change from a short to a long position and vice versa, $riskf_i$ is the risk-free return (4% per annum), and $sell_t$ stands for the sell signals (equal to -1 when we are in a short position and equal to 0 when we are in a long position or we take no market position).

Note that, as technical trading is often criticized on the grounds that the profits generated may be illusory given the existence of transaction costs [see, e. g., Korajczyk and Sadka (2004) and Lesmond *et al.* (2004)], we explicitly incorporate such costs in computing the net returns from our trading strategy based on the price-trend model.

In order to compare the mean net return of the Taylor strategy with the mean net return of the buy and hold strategy the Sharpe ratio is employed. It divides the net return by its standard deviation, which for the series *i* in the period *t* is defined as

$$Sharpe_i^t = \frac{R_i^t / N_{return}}{\sigma_{R_i^t}} \tag{21}$$

where N_{return} represents the number of returns considered in the period.

The buy and hold strategy returns are obtained by adding the returns of the series from the first to the last, and subtracting two transaction costs corresponding with a buy in the first return and a sale in the last return.

Table 4 reports the values of parameters q, k_1 and k_2 for the training period used in Table 3 and the returns, obtained in the prediction period (01-01-2008 until 27-09-2008), by both, the B&H strategy and Taylor's strategy whose parameters are obtained by means of a GA. The Sharpe ratio of both strategies is also reported.

As can be seen in Table 4, for the exchange rates series where the U^* statistic accepted the null hypothesis of random walk at a significant level of 5%, the return obtained by B&H strategy is higher than Taylor's strategy. This lack of predictive power is also confirmed by comparing Sharpe's ratios which are lower for the B&H strategy. Note that for the series where the trend is not accepted, we have not applied Taylor's strategy.

The countries where the U^* statistic rejects the null in favour of trend may be divided into two groups:

- Currencies where Taylor's strategy is not able to improve the B&H strategy, neither in return nor in Sharpe ratios. This happens in 14 out of the 39 cases. For these currencies although, in theory, the trends detected could be employed to beat the market, in practice it does not, at least not in the prediction period considered. Taking into account that sufficient large and long-life trends in prices will make a market inefficient, such markets were probably inefficient during the years studied. However, Taylor's strategy is not able to exploit these inefficiencies with predicting purposes during the period considered in 2008.
- Currencies where Taylor's strategy overcomes the B&H strategy, as much in returns as in Sharpe ratios. This happens in 25 out of the 39 cases and, as can be seen in Figure 3, this behaviour is more frequent in intermediate exchange-rate regimes. These exchange markets were probably inefficient during the years studied, making it possible to exploit slight dependence between returns using Taylor's trend model during 2008 to generate profitable net returns even taking into account transaction costs

5. Concluding remarks

The profitability of technical trading strategies in foreign exchange markets can be explained by a large class of nonlinear prediction rules potentially deriving from nonlinear versions of structural models such as chaos models by Gilmore (1991), target-zone models by Krugman (1991), monetary model by Meese and Rose (1991), Self-Exciting Thereshold Autoregressive model by Krager and Kugler (1993), ARCH based models by Diebold and Pauly (1988), or Markov switching models by Dewachter (2001). Although these models fit in-sample the data with acceptable level, out-o-sample tests of these models indicate that their short-term forecasts have little success with respect to the random walk model. In contrast, this paper provides additional evidence that trading strategies without theoretical foundation are able to improve the predictions of the random walk model, even taking into account the existence of transaction costs. So, the success of technical trading rules in the foreign exchange market constitutes a major puzzle in international finance.

We believe that our paper contributes to the literature by applying a methodological innovation as well as our findings of the presence of economically exploiting trends in exchange rates for a wide sample of countries and exchange-rate regimes.

We have tested for the random walk hypothesis against the existence of trends in 95 exchange rate series against the US Dollar. To that end, we have applied Taylor's (1980) trend price model and Taylor's U^* statistic. The parameters defining the trend were estimated by maximum likelihood by mean of a genetic algorithm. Finally, a technical strategy, proposed by Taylor, devoted to obtaining extraordinary profits in the case of trends in the financial prices, was implemented.

The main results are as follows. First, when using Taylor's *U** statistics, in 39 of the 95 cases considered we find evidence in favour of the presence of trends in exchange rate series for the last known regime, being trends more frequent in intermediate exchange-rate regimes.

Secondly, when deriving optimal one-step-ahead forecasts of returns based on these trends and constructing a trading rule based on these forecasts, we find that Taylor´s strategy overcomes the buy-and-hold strategy in 25 out of 39 cases where trends are detected, even in the presence of transaction costs.

Therefore, this paper has showed the potential usefulness of Taylor's price trend model for technical trading rules to forecast daily exchange data when the model parameters are estimated by maximum likelihood using genetic algorithms.

Facts found here might have both some practical meaning for investors and some theoretical insights for academic scholars interested in the behaviuor of exchange-rate markets.

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Table 1: Summary of the evidence on the presence of exchange-rate trenes using the U* statistic (sample until 31 December 2007)

Currency\Regime	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Euro (from 1999)	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	0
Algeria Dinar	0	0	0	0	0	0	0	-1	0	-1	0	-1	0	-1	0
Angola Adjusted Kwanza	0	0	0	1	0	0	0	0	0	0	0	0	-1	-1	0
Argentina Peso	0	-1	0	0	0	0	0	-1	0	0	0	0	0	-1	-1
Australian Dollar	0	-1	0	0	0	0	0	1	0	0	0	-1	-1	0	0
Bangladesh Taka	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0
Barbados Dollar	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0
Belize Dollar	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0
Buthan Ngultrum	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Bolivia Boliviano	0	0	0	0	0	0	-1	-1	0	-1	0	-1	0	-1	0
Brazil Real	0	-1	0	0	0	-1	0	0	0	-1	0	1	0	-1	0
Brunei Darussalem Ringgit	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Burundi Franc	0	0	0	0	0	0	0	1	0	-1	0	0	0	-1	0
Cambodia Riel	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0
Canada Dollar	0	0	0	0	0	0	0	1	0	-1	0	0	0	0	0
Cape Verde Escudo	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0
Chile Peso	0	-1	0	0	-1	0	0	0	1	1	0	1	0	1	0
China Yuan Renmimbi	0	0	0	-1	0	0	0	-1	0	0	0	-1	0	0	0
Colombia Peso	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0
Congo Democratic Republic Franc	0	0	0	0	0	0	0	0	0	-1	0	-1	-1	-1	0
Costa Rica Colon	0	-1	0	0	0	0	1	1	0	-1	0	-1	0	-1	0
Dominican Republic Peso	0	0	0	0	0	0	0	-1	0	-1	0	-1	0	-1	0
Ecuador Sucre (until 2001)	0	-1	0	0	0	0	0	-1	0	-1	0	-1	0	1	-1
Egypt Pound	0	0	0	-1	0	0	0	0	0	-1	0	0	0	0	0
El Salvador Colon	-1	0	0	-1	0	0	0	-1	0	0	0	-1	0	0	0
Equatorial Guinea Epkwele	0	-1	0	0	0	0	0	-1	0	0	0	0	0	0	0
Ethiopia Birr	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0
Fiji Dollar (USD per FD)	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0
Gambia Dalasi	0	1	0	0	0	0	0	1	0	0	0	0	-1	-1	-1
Ghana New Cedi	0	-1	0	0	0	0	0	1	0	0	0	-1	-1	-1	0
Guinea Franc	0	-1	0	0	0	0	-1	1	0	-1	0	-1	0	-1	1
Guinea-Bissau Escudo/Peso (until 1997)	0	0	0	0	-1	0	0	0	0	0	0	0	0	0	-1
Guyana Dollar	0	0	0	0	0	0	-1	0	0	0	0	0	0	-1	0
Haiti Gourde	0	-1	0	0	0	0	0	-1	0	-1	0	1	-1	1	0
Honduras Lempira	0	-1	0	0	0	0	-1	0	0	-1	0	0	0	-1	0
Hong Kong Dollar	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
India Rupee	0	-1	0	-1	0	0	1	1	0	0	0	-1	0	0	0
Indonesia Rupiah	0	0	0	0	0	0	1	0	0	-1	0	1	0	1	0
Israel New Sequel	0	0	0	0	0	-1	0	1	-1	1	0	-1	0	-1	0
Jamaica Dollar	0	-1	0	-1	0	0	1	-1	0	-1	0	0	0	-1	0
Japan Yen	0	-1	0	0	0	0	0	1	0	0	0	-1	1	0	0
Jordan Dinar	0	-1	0	-1	0	0	-1	0	0	-1	0	0	0	-1	0
Kazakhstan Tenge	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0

Note: See text for the classification of *de facto* exchange-rate regimes.

Table 1 (continued)

Currency\Regime	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Kenya Shilling	0	-1	0	0	0	0	0	1	0	0	0	-1	0	-1	0
South Korea Won	0	-1	0	0	0	-1	1	0	0	1	0	1	0	-1	0
Kuwait Dinar	0	-1	0	-1	0	0	-1	0	0	0	0	0	0	0	0
Kyrgyzstan Som	0	0	0	0	0	0	0	1	0	0	0	0	0	-1	0
Lebanon Pound	0	-1	0	0	0	0	-1	1	0	1	0	0	0	1	0
Leshoto Loti	-1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Madagascar Ariary	0	1	0	0	0	0	0	-1	0	0	0	1	0	-1	-1
Malawi Kwacha	0	1	0	0	0	0	-1	0	0	0	0	1	-1	-1	0
Malaysia Ringgit	0	1	0	0	0	0	0	1	0	0	0	0	-1	0	0
Maldive Islands Rufiyaa (until 1984)	0	-1	0	-1	0	0	0	0	0	0	0	0	0	0	0
Mauritania Ougiyaa	0	1	0	-1	0	0	-1	1	0	-1	0	0	0	0	0
Mauritus Rupee	0	0	0	0	0	0	0	1	0	-1	0	0	0	0	-1
Mexico New Peso	0	-1	0	-1	-1	0	-1	0	-1	0	0	-1	0	1	0
Moldova Leu	0	0	0	-1	0	0	0	1	0	0	0	0	0	1	-1
Mongolia Tugrik	0	0	0	-1	0	0	0	-1	0	0	0	0	-1	-1	0
Morocco Dirham	0	0	0	0	0	0	-1	-1	0	0	0	0	0	0	0
Mozambique New Metical	0	0	0	-1	0	0	0	-1	0	0	0	0	0	0	0
Mianmar (Burma) Kyat	0	-1	0	0	0	0	0	0	0	1	-1	-1	0	1	-1
Namibia Dollar	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0
Nepal Rupee	0	-1	0	0	0	0	0	-1	0	-1	0	0	0	0	0
New Zealand Dollar	0	-1	0	0	0	0	0	1	0	0	0	1	0	0	0
Nicaragua Cordoba Oro	0	-1	-1	0	0	0	-1	-1	0	0	0	0	-1	-1	0
Nigeria Naira	0	-1	0	0	0	0	0	0	0	0	0	1	-1	-1	0
Pakistan Rupee	0	-1	0	0	0	0	-1	-1	0	0	0	0	0	0	-1
Papua New Guinea Kina	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Paraguay Guarani	0	0	0	0	0	0	1	-1	0	1	0	-1	0	-1	0
Peru New Sol	0	0	0	0	0	0	0	1	0	0	0	0	0	-1	-1
Philippines Peso	0	0	0	-1	0	0	-1	1	0	-1	0	-1	0	-1	0
Qatar Ryal	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0
Sao Tome and Principe Dobra	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	0
Saudi Arabia Rial	0	-1	0	1	0	0	0	0	0	0	0	0	0	0	0
Seychelles Rupee	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Sierra Leone Leone	0	0	0	-1	0	0	0	0	0	0	0	0	-1	0	0
Singapore Dollar	0	-1	0	0	0	0	0	0	0	0	1	0	0	0	0
South Africa Rand	0	-1	0	0	0	0	0	0	0	0	0	1	1	0	1
Sri Lanka Rupee	0	-1	0	0	0	-1	1	-1	-1	1	0	-1	0	0	0
Sudan Pound	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0
Suriname Dollar	0	-1	0	0	0	0	0	-1	0	-1	0	-1	0	-1	0
Swaziland Lilangeni	-1	-1	0	1	0	0	0	0	0	0	0	0	0	0	0
Syria Pound	0	0	0	0	0	0	0	-1	0	-1	0	-1	0	0	0
Tajikistan Somoni	0	-1	0	0	0	0	1	0	0	0	0	0	0	-1	0
Tanzania Shilling	0	-1	0	-1	0	0	0	1	0	-1	0	-1	0	1	0
Thailand Baht	0	-1	0	1	0	0	0	0	0	0	1	-1	0	-1	0
Tonga Pa'anga	0	0	0	0	0	0	0	-1	0	0	0	0	0	0	0
Trinidad and Tobago Dollar	0	0	0	0	0	0	-1	0	0	0	0	0	0	0	0
Tunisia Dinar	0	-1	0	0	0	0	0	1	0	0	0	0	0	0	0
United Arab Emirates Dirham	0	-1	0	0	0	0	0	0	0	0	0	0	0	0	0
British Pound	0	1	-1	0	0	0	0	0	0	0	-1	1	0	0	0
Uruguay Peso	0	0	0	0	-1	-1	0	1	0	0	0	1	0	-1	0
Venezuela Bolivar Fuerte	0	-1	0	0	0	1	0	0	0	0	0	1	0	-1	-1
Viet Nam Dong	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Zambia Kwacha	0	-1	0	0	0	0	0	0	0	0	0	-1	-1	1	0

Note: See text for the classification of *de facto* exchange-rate regimes.

Table 2: Summary of the evidence on the presence of exchange-rate trends using the U* statistic (sample until 27 September 2008)

Currences	last regime	data until 12/31/2007	data until 09/27/2008
Euro (from 1999)	14	-1	1
Algeria Dinar	8	-1	-1
Angola Adjusted Kwanza	4	1	1
Argentina Peso	8	-1	1
Australian Dollar	13	1	1
Bangladesh Taka	7	-1	-1
Barbados Dollar	2	-1	-1
Belize Dollar	2	-1	-1
Buthan Ngultrum	2	1	1
Bolivia Boliviano	7	-1	-1
Brazil Real	12	1	1
Brunei Darussalem Ringgit	8	1	1
Burundi Franc	8	1	1
Cambodia Riel	7	-1	-1
Canada Dollar	10	-1	-1
Cape Verde Escudo	7	-1	-1
Chile Peso	10	1	1
China Yuan Renmimbi	4	-1	-1
Colombia Peso	10	1	1
Congo Democratic Republic Franc	13	-1	-1
Costa Rica Colon	7	1	1
Dominican Republic Peso	12	-1	-1
Ecuador Sucre (until 2001)	14	1	1
Egypt Pound	4	-1	-1
El Salvador Colon	1	-1	-1
Equatorial Guinea Epkwele	2	-1	-1
Ethiopia Birr	7	-1	-1
Fiji Dollar	10	-1	-1
Gambia Dalasi	8	1	1
Ghana New Cedi	8	1	-1
Guinea Franc	10	-1	-1
Guinea-Bissau Escudo/Peso (until 1997)	15	-1	-1
Guyana Dollar	7	-1	-1
Haiti Gourde	12	1	1
Honduras Lempira	7	-1	-1
Hong Kong Dollar	2	1	1
India Rupee	8	1	1
Indonesia Rupiah	12	1	1
Israel New Sequel	10	1	1
Jamaica Dollar	7	1	-1
Japan Yen	13	1	1
Jordan Dinar	4	-1	-1
Kazakhstan Tenge	8	1	1
Kenya Shilling	8	1	1

Note: See text for the classification of *de facto* exchange-rate regimes.

Table 2 (continued)

Currences	last regime	data until 12/31/2007	data until 09/27/2008
South Korea Won	12	1	1
Kuwait Dinar	4	-1	1
Kyrgyzstan Som	8	1	1
Lebanon Pound	2	-1	-1
Leshoto Loti	2	1	1
Madagascar Ariary	12	1	1
Malawi Kwacha	7	-1	-1
Malaysia Ringgit	8	1	1
Maldive Islands Rufiyaa (until 1984)	4	-1	-1
Mauritania Ougiyaa	7	-1	-1
Mauritus Rupee	8	1	1
Mexico New Peso	12	-1	-1
Moldova Leu	8	1	1
Mongolia Tugrik	4	-1	1
Morocco Dirham	7	-1	1
Mozambique New Metical	8	-1	-1
Mianmar (Burma) Kyat	15	-1	-1
Namibia Dollar	2	-1	-1
Nepal Rupee	8	-1	1
New Zealand Dollar	12	1	1
Nicaragua Cordoba Oro	7	-1	-1
Nigeria Naira	12	1	1
Pakistan Rupee	7	-1	-1
Papua New Guinea Kina	7	1	1
Paraguay Guarani	10	1	1
Peru New Sol	8	1	1
Philippines Peso	8	1	1
Qatar Ryal	2	-1	-1
Sao Tome and Principe Dobra	10	-1	-1
Saudi Arabia Rial	4	1	1
Seychelles Rupee	8	1	1
Sierra Leone Leone	4	-1	-1
Singapore Dollar	11	1	1
South Africa Rand	13	1	1
Sri Lanka Rupee	7	1	1
Sudan Pound	7	-1	-1
Suriname Dollar	2	-1	-1
Swaziland Lilangeni	2	-1	-1
Syria Pound	10	-1	-1
Tajikistan Somoni	7	1	1
Tanzania Shilling	10	-1	-1
Thailand Baht	11	1	1
Tonga Pa'anga	8	-1	-1
Trinidad and Tobago Dollar	7	-1	-1
Tunisia Dinar	8	1	1
United Arab Emirates Dirham	2	-1	-1
British Pound	11	-1	1
Uruguay Peso	8	1	1
Venezuela Bolivar Fuerte	15	-1	-1
Viet Nam Dong	7	1	1
Zambia Kwacha	13	-1	-1

Note: See text for the classification of *de facto* exchange-rate regimes.

Table 3: Taylor's statistics and trend parameters

Currencies	Last regime	Initial date	Final date	U*	A	p	m
Euro	14	11062007	12312007	-0.3778	0	0	0
Algeria Dinar	8	11062007	12312007	-0.5152	0	0	0
Angola Adjusted Kwanza	4	7202005	12312007	1.6615	0.1216	0.7072	3
Argentina Peso	8	11062007	12312007	-1.1554	0	0	0
Australian Dollar	13	11062007	12312007	-0.2062	0	0	0
Bangladesh Taka	7	11062007	12312007	-0.4555	0	0	0
Barbados Dollar	2	11062007	12312007	0.0000	0	0	0
Belize Dollar	2	11062007	12312007	0.0000	0	0	0
Buthan Ngultrum	2	8112004	12312007	2.2324914	0.02638808	0.95237738	20.9984245
Bolivia Boliviano	7	11062007	12312007	0.0000	0	0	0
Brazil Real	12	10011999	12312007	2.1350	0.0134	0.9858	70
Brunei Darussalem Ringgit	8	2011990	12312007	4.3782	0.0134	0.9911	113
Burundi Franc	8	3242006	12312007	2.568965893	0.0560163	0.90872455	10.9558484
Cambodia Riel	7	11062007	12312007	0.2519	0	0	0
Canada Dollar	10	11062007	12312007	-0.7328	0	0	0
Cape Verde Escudo	7	11062007	12312007	-0.5032	0	0	0
Chile Peso	10	2012002	12312007	2.9770	0.0489	0.8809	8
China Yuan Renmimbi	4	11062007	12312007	-0.3220	0	0	0
Colombia Peso	10	1021985	12312007	23.6481	0.0607	0.9979	465
Congo Democratic Republic Franc	13	10292007	12312007	0.0611	0	0	0
Costa Rica Colon	7	2012002	12312007	2.0314	0.0138	0.9980	512
Dominican Republic Peso	12	11062007	12312007	0.0391	0	0	0
Ecuador Sucre	14	9102001	11022001	0.0000	0	0	0
Egypt Pound	4	11222007	12312007	-0.5040	0	0	0
El Salvador Colon	1	11062007	12312007	0.0000	0	0	0
Equatorial Guinea Epkwele	2	9171986	11111986	-0.6719	0	0	0
Ethiopia Birr	7	11062007	12312007	0.0000	0	0	0
Fiji Dollar (USD per FD)	10	11062007	12312007	-0.5813	0	0	0
Gambia Dalasi	8	5112007	12312007	1.6774	0.0464	0.9389	16
Ghana New Cedi	8	6042007	12312007	4.170444834	0.10777243	0.95284192	21.2052717
Guinea Franc	10	11062007	12312007	0.0588	0	0	0
Guinea-Bissau Escudo/Peso	15	11062007	12312007	0.0000	0	0	0
Guyana Dollar	7	11062007	12312007	0.3133	0	0	0
Haiti Gourde	12	4052007	12312007	1.705477566	0.04337436	0.94006856	16.6857328
Honduras Lempira	7	11062007	12312007	-0.0925	0	0	0
Hong Kong Dollar	2	4162007	12312007	1.7206	0.0721	0.8715	8
India Rupee	8	2012005	12312007	2.470463417	0.02465232	0.95318002	21.3584013
Indonesia Rupiah	12	5031999	12312007	3.3993	0.0527	0.8815	8
Israel New Sequel	10	3011991	12312007	3.4449	0.0223	0.9198	12
Jamaica Dollar	7	6142007	12312007	1.7064	0.2987	0.6303	3
Japan Yen	13	1031978	12312007	5.0840	0.0221	0.9373	16
Jordan Dinar	4	11062007	12312007	-0.6463	0	0	0
Kazakhstan Tenge	8	8012005	12312007	3.6718	0.0663	0.9390	16
Kenya Shilling	8	2011996	12312007	3.9789	0.1732	0.5176	2

Notes:

a. All calculations were carried out from the beginning of the series until 27 September 2008
b. The parameters A and p [m=1/(1-p)] were obtained through maximizing the logarithm of likelihood function by a genetic algorithm.
c. In blue, the *U** statistic rejects the null in favour of trend at the 5% confidence level.
d. See text for the classification of *de facto* exchange-rate regimes.

Table 3 (continued)

Currencies	Last regime	Initial date	Final date	U*	A	p	m
South Korea Won	12	8031998	12312007	2.7173	0.0353	0.8536	7
Kuwait Dinar	4	11222007	12312007	-0.6618	0	0	0
Kyrgyzstan Som	8	8072007	12312007	2.5968	0.0736	0.9713	35
Lebanon Pound	2	11062007	12312007	0.0205	0	0	0
Leshoto Loti	2	5082000	12312007	1.7028	0.0106	0.9883	85
Madagascar Ariary	12	2021999	12312007	2.0820	0.0080	0.9738	38
Malawi Kwacha	7	11062007	12312007	-0.2968	0	0	0
Malaysia Ringgit	8	11062007	12312007	-1.0430	0	0	0
Maldive Islands Rufiyaa	4	11062007	12312007	-0.6685	0	0	0
Mauritania Ougiyaa	7	11062007	12312007	-0.2448	0	0	0
Mauritus Rupee	8	4082002	12312007	3.2323	0.0090	0.9966	290
Mexico New Peso	12	11062007	12312007	-0.1758	0	0	0
Moldova Leu	8	4032000	12312007	13.4773	0.1224	0.9445	18
Mongolia Tugrik	4	11062007	12312007	-0.1417	0	0	0
Morocco Dirham	7	11062007	12312007	-0.4420	0	0	0
Mozambique New Metical	8	11022007	12312007	-0.5163	0	0	0
Mianmar (Burma) Kyat	15	11062007	12312007	0.0000	0	0	0
Namibia Dollar	2	11062007	12312007	-1.1625	0	0	0
Nepal Rupee	8	11062007	12312007	-0.2180	0	0	0
New Zealand Dollar	12	3221994	12312007	1.6545	0.0122	0.9821	56
Nicaragua Cordoba Oro	7	11062007	12312007	0.0430	0	0	0
Nigeria Naira	12	10031996	12312007	1.7528	0.0003	0.9980	494
Pakistan Rupee	7	11062007	12312007	0.1947	0	0	0
Papua New Guinea Kina	7	2011990	12312007	1.8081	0.0070	0.9735	38
Paraguay Guarani	10	4142005	12312007	1.6760	0.1127	0.7389	4
Peru New Sol	8	12011993	12312007	3.9348	0.0160	0.9936	156
Philippines Peso	8	1032000	12312007	3.6923	0.0172	0.9933	150
Qatar Ryal	2	11222007	12312007	-0.7693	0	0	0
Sao Tome and Principe Dobra	10	11062007	12312007	-0.3100	0	0	0
Saudi Arabia Rial	4	11171980	12312007	2.0420	0.0069	0.9887	89
Seychelles Rupee	8	12222006	12312007	1.6681	0.0664	0.8413	6
Sierra Leone Leone	4	11062007	12312007	-0.6095	0	0	0
Singapore Dollar	11	9171973	12312007	1.7808	0.0008	0.9860	71
South Africa Rand	13	4031995	12312007	2.3190	0.6210	0.1273	0
Sri Lanka Rupee	7	6012001	12312007	2.9840	0.9999	0.1601	0
Sudan Pound	7	11022007	12312007	-0.7243	0	0	0
Suriname Dollar	2	10292007	12312007	0.0000	0	0	0
Swaziland Lilangeni	2	11062007	12312007	-1.1661	0	0	0
Syria Pound	10	11062007	12312007	0.0000	0	0	0
Tajikistan Somoni	7	1272005	12312007	3.9395	0.0390	0.9531	21
Tanzania Shilling	10	11062007	12312007	0.0326	0	0	0
Thailand Baht	11	11011999	12312007	4.0850	0.0238	0.9653	29
Tonga Pa'anga	8	11062007	12312007	-1.2339	0	0	0
Trinidad and Tobago Dollar	7	11062007	12312007	-0.3101	0	0	0
Tunisia Dinar	8	3311977	12312007	2.4425	0.0027	0.9197	12
United Arab Emirates Dirham	2	10292007	12312007	0.3601	0	0	0
British Pound	11	11062007	12312007	-0.6628	0	0	0
Uruguay Peso	8	9252006	12312007	1.8378	0.1185	0.7975	5
Venezuela Bolivar Fuerte	15	10292007	12312007	0.0000	0	0	0
Viet Nam Dong	7	2012002	12312007	2.6170	0.0078	0.9904	105
Zambia Kwacha	13	11062007	12312007	-0.7285	0	0	0

Notes:

a. The training period used in the calculations spans from that indicated in the column "initial date" to that in the "final date". The prediction period spans from the day after that indicated in the column "final date" to 27 September 2008
b. The parameters A and p [m=1/(1-p)] were obtained through maximizing the logarithm of likelihood function by a genetic algorithm.
c. In blue, the $U*$ statistic rejects the null in favour of trend at the 5% confidence level.
d. See text for the classification of *de facto* exchange-rate regimes.

Table 4: Parameters of Taylor's strategy and prediction performance statistics

Currencies	q	k1	k2	B&H	Sharpe B&H	Taylor	Sharpe Taylor
Euro	0	0	0	0.0081	0.0077	0	0
Algeria Dinar	0	0	0	-0.0826	-0.0856	0	0
Angola Adjusted Kwanza	0.6288	1.0973	-1.4009	-0.0010	-0.0183	-0.0007	-0.0123
Argentina Peso	0	0	0	-0.0412	-0.1350	0	0
Australian Dollar	0	0	0	-0.0218	-0.0168	0	0
Bangladesh Taka	0	0	0	0.0031	0.0306	0	0
Barbados Dollar	0	0	0	0.0040	0.0651	0	0
Belize Dollar	0	0	0	-0.0015	-0.0084	0	0
Buthan Ngultrum	0.9316	1.6548	-1.4455	0.1000	0.1710	0.0286	0.0503
Bolivia Boliviano	0	0	0	-0.0729	-0.1619	0	0
Brazil Real	0.9759	0.6231	-0.1461	-0.0930	-0.0689	0.1034	0.0896
Brunei Darussalem Ringgit	0.9822	1.2265	-0.0517	-0.0215	-0.0415	0.0169	0.0351
Burundi Franc	0.8666	0.7009	-0.1473	0.0581	0.0948	-0.0313	-0.0656
Cambodia Riel	0	0	0	0.0387	0.0587	0	0
Canada Dollar	0	0	0	0.0528	0.0488	0	0
Cape Verde Escudo	0	0	0	-0.0099	-0.0103	0	0
Chile Peso	0.8431	0.1757	-0.7009	0.0396	0.0271	0.0838	0.0619
China Yuan Renmimbi	0	0	0	-0.0670	-0.3056	0	0
Colombia Peso	0.9833	0.0500	-0.0252	-0.0610	-0.0371	0.1024	0.0650
Congo Democratic Republic Franc	0	0	0	0.0080	0.0181	0	0
Costa Rica Colon	0.9924	0.0653	-1.6908	0.1110	0.1989	0.1093	0.2023
Dominican Republic Peso	0	0	0	0.0504	0.1180	0	0
Ecuador Sucre	0	0	0	0.0000	0.0000	0	0
Egypt Pound	0	0	0	-0.0272	-0.0667	0	0
El Salvador Colon	0	0	0	-0.0007	-0.1559	0	0
Equatorial Guinea Epkwele	0	0	0	-0.0258	-0.0608	0	0
Ethiopia Birr	0	0	0	0.0564	0.1722	0	0
Fiji Dollar (USD per FD)	0	0	0	-0.0147	-0.0176	0	0
Gambia Dalasi	0.9044	1.2286	-0.3230	0.0461	0.0301	0.1944	0.1831
Ghana New Cedi	0.8884	1.1623	-1.6024	0.1150	0.3954	0.1053	0.3615
Guinea Franc	0	0	0	0.0588	0.0720	0	0
Guinea-Bissau Escudo/Peso	0	0	0	0.0000	0.0000	0	0
Guyana Dollar	0	0	0	0.0062	0.0143	0	0
Haiti Gourde	0.9075	0.6771	-0.9062	0.0708	0.1696	0.0482	0.1417
Honduras Lempira	0	0	0	0.0038	0.0105	0	0
Hong Kong Dollar	0.8182	1.9221	-0.8663	0.0000	0.0002	0.0144	0.2278
India Rupee	0.9336	0.4619	-0.0105	0.1010	0.1394	0.0681	0.0965
Indonesia Rupiah	0.8412	0.6069	-0.0118	-0.0263	-0.0608	0.0415	0.1058
Israel New Sequel	0.9012	0.8238	-0.1280	-0.0762	-0.0495	-0.0207	-0.0142
Jamaica Dollar	0.4626	1.9914	-0.6054	0.0174	0.0658	0.0143	0.1173
Japan Yen	0.9191	0.6894	-0.0358	-0.0195	-0.0155	-0.0865	-0.0730
Jordan Dinar	0	0	0	-0.0006	-0.0039	0	0
Kazakhstan Tenge	0.8926	0.4669	-0.2301	-0.0084	-0.0680	-0.0019	-0.0164
Kenya Shilling	0.4322	1.2435	-0.4127	0.0716	0.0333	-0.0728	-0.0483

Notes:

a. The training period used in the calculations spans from that indicated in the column "initial date" to that in the "final date". The prediction period spans from the day after that indicated in the column "final date" to 27 September 2008
b. The parameters of Taylor's strategy were obtained through maximizing the Sharpe ratio by a genetic algorithm.
c. In blue, the *U** statistic rejects the null in favour of trend at the 5% confidence level, but Taylor's strategy is not able to improve the B&H strategy.
d. In orange, the *U** statistic rejects the null in favour of trend at the 5% confidence level, and Taylor's strategy overcomes the B&H strategy.

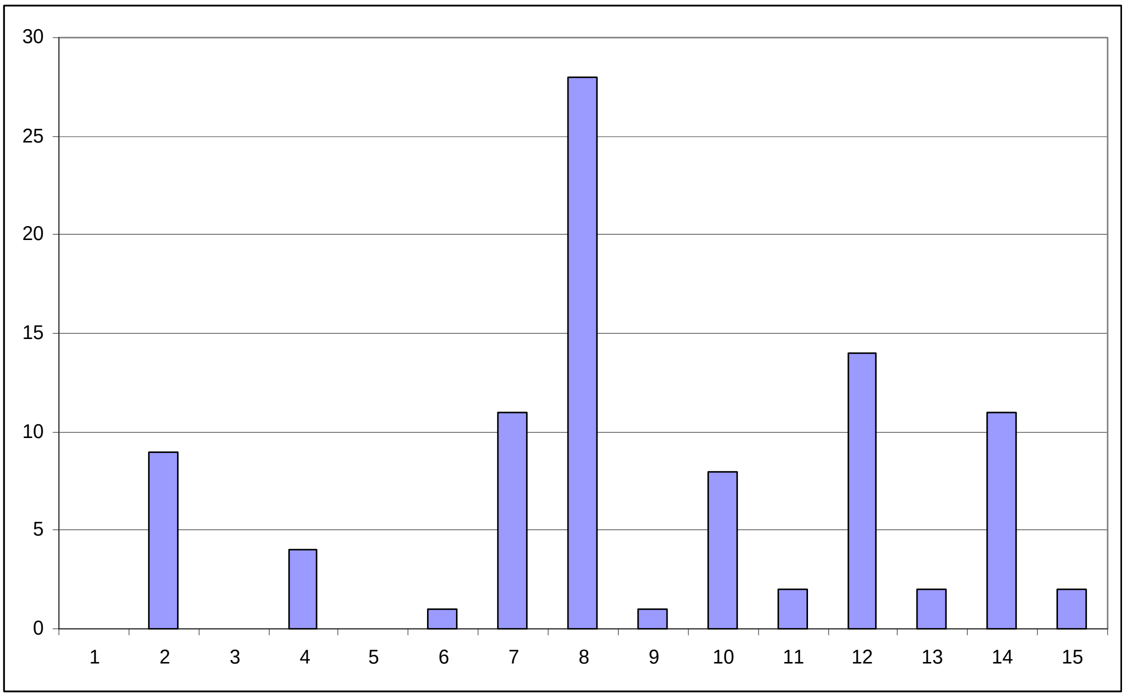
Table 4 (continued)

Currencies	q	k1	k2	B&H	Sharpe B&H	Taylor	Sharpe Taylor
South Korea Won	0.8258	1.6384	-0.0429	0.1460	0.1229	0.0842	0.0719
Kuwait Dinar	0	0	0	-0.0232	-0.0704	0	0
Kyrgyzstan Som	0.9287	0.6811	-0.1067	-0.0215	-0.0313	0.0508	0.0774
Lebanon Pound	0	0	0	-0.0042	-0.0504	0	0
Leshoto Loti	0.9804	0.5634	-0.0718	0.1361	0.0672	-0.0714	-0.0421
Madagascar Ariary	0.9669	0.8699	-0.1247	-0.0896	-0.1461	0.0925	0.1574
Malawi Kwacha	0	0	0	0.0222	0.0558	0	0
Malaysia Ringgit	0	0	0	0.0206	0.0305	0	0
Maldive Islands Rufiyaa	0	0	0	0.0124	0.0750	0	0
Mauritania Ougiyaa	0	0	0	-0.0907	-0.1858	0	0
Mauritus Rupee	0.9914	1.2347	-0.7250	0.0318	0.0355	0.0015	0.0022
Mexico New Peso	0	0	0	-0.0729	-0.1160	0	0
Moldova Leu	0.8707	1.0659	-0.1055	-0.1620	-0.4139	0.1689	0.4505
Mongolia Tugrik	0	0	0	-0.0155	-0.2092	0	0
Morocco Dirham	0	0	0	5.3454	0.0808	0	0
Mozambique New Metical	0	0	0	-11.2791	-0.0491	0	0
Mianmar (Burma) Kyat	0	0	0	0.0000	0.0000	0	0
Namibia Dollar	0	0	0	0.1273	0.0678	0	0
Nepal Rupee	0	0	0	0.0980	0.1516	0	0
New Zealand Dollar	0.9725	0.8684	-0.0735	-0.0907	-0.0671	0.0268	0.0236
Nicaragua Cordoba Oro	0	0	0	-3.3268	-0.0796	0	0
Nigeria Naira	0.9977	0.8403	-0.1327	-0.0047	-0.0327	0.0163	0.1715
Pakistan Rupee	0	0	0	0.2013	0.1632	0	0
Papua New Guinea Kina	0.9674	0.5295	-0.3155	0.0839	0.2011	-0.0080	-0.0193
Paraguay Guarani	0.6637	1.0996	-0.1296	-0.1766	-0.2685	0.1715	0.2703
Peru New Sol	0.9843	1.3296	-0.0820	-0.0158	-0.0151	0.0148	0.0148
Philippines Peso	0.9834	0.2385	-0.0077	0.1000	0.1100	0.0865	0.1015
Qatar Ryal	0	0	0	-0.0010	-0.0115	0	0
Sao Tome and Principe Dobra	0	0	0	0.0362	0.0720	0	0
Saudi Arabia Rial	0.9832	1.3994	-0.0360	-0.0007	-0.0097	0.0342	0.4572
Seychelles Rupee	0.7919	0.0165	-0.0198	0.0009	0.0125	0.0059	0.0855
Sierra Leone Leone	0	0	0	0.0081	0.0400	0	0
Singapore Dollar	0.9852	0.6078	-0.4699	-0.0159	-0.0271	0.0537	0.0993
South Africa Rand	0.0486	0.7426	-0.0711	0.1227	0.0620	0.0852	0.0464
Sri Lanka Rupee	0.0000	1.4485	-0.8164	-0.0091	-0.0692	0.0008	0.0067
Sudan Pound	0	0	0	0.0234	0.0432	0	0
Suriname Dollar	0	0	0	-0.0065	-0.0444	0	0
Swaziland Lilangeni	0	0	0	0.1274	0.0665	0	0
Syria Pound	0	0	0	-0.0018	-0.0413	0	0
Tajikistan Somoni	0.9242	0.7146	-0.5408	-0.0144	-0.1930	0.0290	0.4286
Tanzania Shilling	0	0	0	0.0077	0.0082	0	0
Thailand Baht	0.9470	1.0524	-0.1202	0.1284	0.0985	0.0399	0.0326
Tonga Pa'anga	0	0	0	0.0232	0.0261	0	0
Trinidad and Tobago Dollar	0	0	0	-0.0073	-0.0111	0	0
Tunisia Dinar	0.9173	1.3829	-1.7782	-0.0015	-0.0017	0.0353	0.0462
United Arab Emirates Dirham	0	0	0	-0.0011	-0.0699	0	0
British Pound	0	0	0	-0.0804	-0.0881	0	0
Uruguay Peso	0.7158	0.1159	-1.1663	-0.1131	-0.2646	0.0222	0.0634
Venezuela Bolivar Fuerte	0	0	0	0.0000	0.0000	0	0
Viet Nam Dong	0.9845	0.1441	-0.0734	0.0348	0.0878	0.0278	0.0707
Zambia Kwacha	0	0	0	-0.0610	-0.0439	0	0

Notes:

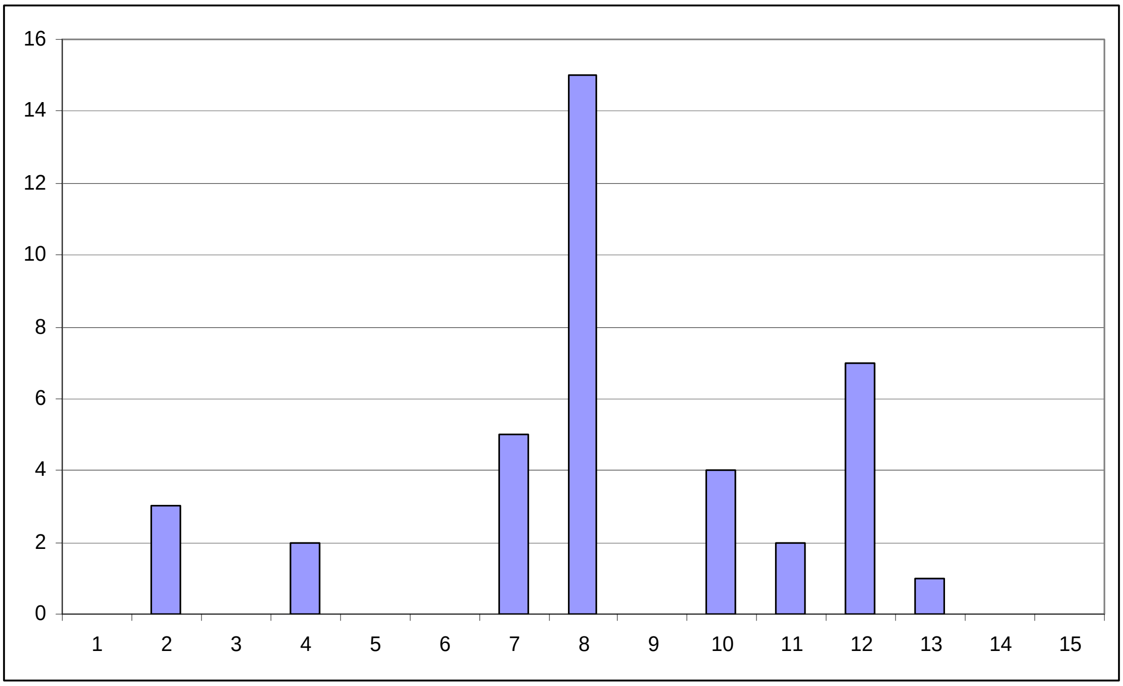
a. The predictions period ranks from 01-01-2008 until 27-09-2008.
b. The parameters of Taylor's strategy were obtained through maximizing the Sharpe ratio by a genetic algorithm.
c. In blue, the *U** statistic rejects the null in favour of trend at the 5% confidence level, but Taylor's strategy is not able to improve the B&H strategy.
d. In orange, the *U** statistic rejects the null in favour of trend at the 5% confidence level, and Taylor's strategy overcomes the B&H strategy.

Figure 1: Detected exchange-rate trends and exchange-rate regimes



Note: See text for the classification of *de facto* exchange-rate regimes.

Figure 2: Detected exchange-rate trends and exchange-rate regimes



Note: See text for the classification of *de facto* exchange-rate regimes.