# Exploiting trends in the foreign exchange markets

Adrián Fernández-Pérez
Departmento de Métodos Cuantitativos, Facultad de Ciencias Económicas y Empresariales, Universidad de Las Palmas de Gran Canaria, Campus de Tafira, 35017 Las Palmas de Gran Canaria Spain, adrian.fernandez102@alu.ulpgc.es

Fernando Fernández-Rodríguez
Departmento de Métodos Cuantitativos, Facultad de Ciencias Económicas y Empresariales, Universidad de Las Palmas de Gran Canaria, Campus de Tafira, 35017 Las Palmas de Gran Canaria Spain, ffernandez@dmc.ulpgc.es

Corresponding author: Simón Sosvilla-Rivero
Departmento de Economía Cuantitativa, Facultad de Ciencias Económicas y Empresariales, Universidad Complutense de Madrid, Campus de Somosaguas, 28223 Madrid, Spain, sosvilla@ccee.ucm.es

## Abstract

We offer further evidence on the relevance of technical trading in exchange rate markets using daily data for 95 currencies against the US Dollar. To that end, we investigate the profitability of a simple technical trading rule based on Taylor (1980)´s price trend model, generating optimal one-step-ahead forecasts of returns using genetic algorithms. 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.

JEL classification numbers: C53, F31, G14.

KEY WORDS: Exchange rates, Price trend model, Genetic algorithms, Trading rules

## 1. Introduction

In the companion paper (Fernández-Pérez *et. al*, 2011), we tested for the existence of trends in exchange rate series for 95 currencies against the US Dollar. To that end, we made use of Taylor (1980)´s price trend model that concentrates on the short-term pattern of the price trend and, employing a maximum likelihood method and a genetic algorithm to estimate the model, we found evidence in favour of the presence of trends in 39 of the 95 cases considered, being trends more frequent in intermediate exchange-rate regimes.

In the present paper we undertake the analysis of the profitability of a simple technical trading rule based on Taylor´s price trend model. To that end, optimal one-step-ahead forecasts of returns are derived using a genetic algorithm and trading rules based on these forecasts are constructed. We have applied this investment strategy to daily data on ninety-five countries from 4 January 1993 to 31 December 2010.

The rest of the paper is organised as follows. Section 2 presents Taylor (1980)´s price trend model. Section 3 describes the data set and reports our empirical results. Finally, Section 4 provides some concluding remarks.

## 2. Taylor’s price rend model

Taylor (1980)’s trend model for a prices time series $P_t$ is defined as

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

where the white noise series $\varepsilon_t$ is uncorrelated with the stochastic process $\mu_t$ representing the trend in the model and it is interpreted as the response to anticipated changes in the supply and demand of the assets. This $\mu_t$ may be positive or negative giving rise to increasing or decreasing price trends. We also define $\sigma^2$ as the variance of $\varepsilon_t$, $v^2$ as the variance of $\mu_t$ and $\bar{\mu}$ as the expectation of $\mu_t$.

So, the trend model may be formulated with probability as

$$\mu_t = \begin{cases} \mu_{t-1} & \text{with probability} \quad p \\ \bar{\mu} + \eta_t & \text{with probability} \quad 1-p \end{cases} \tag{2}$$

where $\eta_t$ is white noise with mean zero and independent of the past trend values $\mu_s$ for $s < t$.

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

$$m = \sum_{i=1}^{\infty} i(1-p)p^{i-1} = (1-p)^{-1} \tag{3}$$

Omitting technical details which can be found in Taylor and Kingsman (1978), Taylor (1980) and Taylor (2008), the base of the price trend test is the existence of positive correlations between daily rescaled returns $x_t / \hat{a}_t$ with several lags, where $\hat{a}_t$ represents the estimation of the mean absolute deviation which is considered a proxy of the variance of the returns $x_t$. On the contrary, in the random walk model, all correlations will be zero for any lag.

The correlations of daily rescaled returns are defined as $\rho_i = cor(x_t / \hat{a}_t, x_{t+1} / \hat{a}_{t+1})$. Taylor shows that model (1) with $\mu_t$ variable as in (2) provides the following correlation expression for rescaled returns

$$\rho_i = \frac{p^i v^2}{v^2 + \sigma^2} = Ap^i, \tag{4}$$

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

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

$$H_0 : \rho_i = 0, \text{ for each i>0} \tag{5}$$

meanwhile the alternative hypothesis to the random walk model is:

$$H_1 : \rho_i = Ap^i, \text{ for some } A \geq 0,\ 0 \leq p \leq 1, \text{ for each i>0} \tag{6}$$

The parameter $A$ is a measure of information that is not instantaneously reflected in the market prices, meanwhile $p$ measures the speed at which the information is reflected in them. If $A$ or $p$ 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.

Due to the complexity of the log likelihood function, in order to estimate the parameters, a genetic algorithm is employed [see Dorsey and Mayer (1995) for the use of genetic algorithms for optimizing complex likelihood functions in econometrics]. 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

$$k_t = \frac{f_{t-1,1}}{\hat{\sigma}_{F,t-1}} \tag{7}$$

where

$$f_{t-1,1} = (\hat{a}_t / \hat{a}_{t-1})\left\{(p-q)x_{t-1} + qf_{t-2,1}\right\} \tag{8}$$

$$\hat{\sigma}_{F,t-1} = \hat{a}_t \left\{ Ap(p-q)/(1-pq)\right\}^{1/2} \tag{9}$$

with $t = 21,...,n_{rend}$, being $n_{rend}$, the total number of returns. In the recursion (8), $f_{t,1}$ 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.

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 (8) and (9). 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 genetic algorithm 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

$$R_i^t = \sum_{t=21}^{N_{rend}} (x_t \, buy_t) + \sum_{t=21}^{N_{rend}} \left[ \left( x_t - riskf_i \right) sell_t \right] - c_i mov_t \tag{10}$$

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

$$Sharpe_i^t = \frac{R_i^t / N_{return}}{\sigma_{R_i^t}} \quad (11)$$

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.

## 3. Data and empirical results

In this paper use 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.

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 2010 by Ilzetzki, Reinhart and Rogoff (2011), to distinguish between a wide range of *de facto* regimes:

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

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

15. Dual market in which parallel market data is missing.

Table 1 reports the values of parameters $q$, $k_1$ and $k_2$ for the training period and the returns, obtained in the prediction period (01-01-2008 until 31-12-2010), by both, the B&H strategy and Taylor's strategy whose parameters are obtained by means of a genetic algorithm. The Sharpe ratio of both strategies is also reported.

As can be seen in Table 1, for the exchange rates series where the null hypothesis of random walk was rejected 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 null in favour of trend is rejected 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 prediction period.
- 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 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 after the trading period to generate profitable net returns even taking into account transaction costs

## 4. 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.

The results in this paper indicate that there exists potential for investors to generate excess returns in exchange rate markets by adopting technical trading rules based one-step-ahead forecasts of returns produced by Taylor (1980)'s price trend model. In particular, 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.

**Acknowledgements**

The authors would like to thank Ethan Ilzetzki for providing us with the updated database on exchange rate arrangements. The authors gratefully acknowledge financial support from the Spanish Ministry of Science and Innovation, through the research projects ECO2008-05565 and ECO2010-21318. Adrián Fernández-Pérez also acknowledges the financial support from INNOVA CANARIAS 2020.

**References:**


Chang, K. P. and Osler, C. (1999) Methodical madness: Technical analysis and the internationality of exchange-rate forecasts. The Economic Journal **109**, 636-661.

Dewachter, H. (2001) Can Markov switching models replicate chartist profits in the foreign exchange market?, *Journal of International Money and Finance*, **20**, 25-41,

Dooley, M. P., Schafer, S. (1983) Analysis of short-run exchange rate behavior: March 1973–November 1981, in: Bigman, D., Taya, T. (Eds.), Exchange Rate and Trade Instability: Causes, Consequences and Remedies. Ballinger, Cambridge, MA, pp. 43-72.

Dorsey, R. D., Mayer, J. M. (1995) Genetic algorithms for estimation problems with multiple optima, nondiferentiability, and other irregular features. *Journal of Business and Economic Statistics* **13**, 53-66.

Fernández-Pérez, A., Fernández-Rodríguez, F. and Sosvilla-Rivero, S. (2011): Detecting trends in the foreign exchange markets, forthcoming in *Applied Economics Letters*.

Gençay, R. (1999) Linear, non-linear and essential foreign exchange rate prediction with simple technical trading rules. *Journal of International Economics* **47**, 91-107.

Harris, R. D. F., Yilmaz, F. (2009) A momentum trading strategy based on the low frequency component of the exchange rate. *Journal of Banking and Finance* **33**, 1575-1585.

Ilzetzki, E. O., Reinhart, C. M, Rogoff, K. S. (2011) Exchange rate arrangements entering the 21st century: which anchor will hold?, mimeo.

Korajczyk, R.E., Sadka, R. (2004) Are momentum profits robust to trading costs? *Journal of Finance* **59**, 1039–1082.

LeBaron, B. (1998) Technical trading rules and regime shifts in foreign exchange, in: Acar, E., Satchell, S. (Eds.), Advanced Trading Rules. Butterworth-Heinemann, Oxford, pp. 5-40.

Lesmond, D. A., Schill, M. J., Zhou, C. (2004) The illusory nature of momentum profits. *Journal of Financial Economics* **71**, 349–380.

Levich, R. M., Thomas, L. R. (1993) The significance of technical trading-rule profits in the foreign exchange market: A bootstrap approach. *Journal of International Money and Finance* **12**, 451-474.

Neely, C., Weller, P., Dittmar, R. (1997) Is technical analysis in the foreign exchange market profitable? A genetic programming approach. *Journal of Financial and Quantitative Analysis* **32**, 405-426.

Reinhart, C. M., Rogoff, K. S. (2004) The modern History of exchange rate arrangements: A reinterpretation. *Quarterly Journal of Economics* **119**, 1-48.

Taylor, S. (1980) Conjectured models for trends in financial prices, tests and forecasts. *Journal of the Royal Statistical Society*. *Series A* **13**, 338-362.

Taylor, S. (2008) Modelling Financial Time Series. World Scientific, New Jersey.

Taylor, S., Kingsman, B. G. (1978) Non-stationarity in sugar prices. *The Journal of the Operational Research Society* **29**, 971-980.

Table 1: 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 31 December 2010

b. The parameters of Taylor's strategy were obtained through maximizing the Sharpe ratio by a genetic algorithm.

c. In blue, evidence of trend is found at the 5% confidence level, but Taylor's strategy is not able to improve the B&H strategy.

d. In orange, evidence of trend is found at the 5% confidence level, and Taylor's strategy overcomes the B&H strategy.

Table 1 (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 31-12-2010.
b. The parameters of Taylor’s strategy were obtained through maximizing the Sharpe ratio by a genetic algorithm.
c. In blue, evidence of trend is found at the 5% confidence level, but Taylor’s strategy is not able to improve the B&H strategy.
d. In orange, evidence of trend is found at the 5% confidence level, and Taylor’s strategy overcomes the B&H strategy.