DO TRENDS EXIST IN THE STOCK MARKETS: AN ANALYSIS BASED ON TAYLOR´S METHODOLOGY

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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. In an alternative way, the defenders of technical analysis maintain that prices move following trends. It means that when new information arrives on the market it does not immediately translate into prices and a certain amount of time is necessary until the market incorporates this information. This situation will reflect that the market will move through trends which may be used in a profitable way using a technical 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 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. Nevertheless, recent studies reveal that there are situations 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. Finally, Kwan et al. (2000) found predictability and profitability considering the price trend model by Taylor (1980) in the Hang Seng Index Futures in Hong Kong.

2. Taylor's trend model

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

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

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 work, Taylor (1980) introduces a trend model permitting 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

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

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 supposes:

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.

So, the trend model may be formulated with probability as

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

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, $\text{var}(x_t) = \Sigma_t^2$.

Besides, it is reasonable to suppose that as much $\text{var}(\varepsilon_t)$ as $\text{var}(\mu_t)$ 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 (1986) 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 $R = \text{var}(\mu_t)/\text{var}(\varepsilon_t)$ 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,

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

From equation (5) it follows that the variance of daily returns are roughly constant, which will facilitate carrying out statistical tests.

In order to estimate Σ_t and given that its relation with the mean absolute deviation a_t is

$$a_t = E\left|X_t\right| = \Sigma_t \ \textit{multiplied by a constant}$$

Taylor prefers to estimate a_t rather than Σ_t. So a_t is estimated using an exponential weighted moving average of the past absolute price changes,

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

coming to the conclusion that the parameter γ, obtained by the maximum likelihood method, is equal to 0.04 for assets and asset indexes.

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

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

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

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

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

meanwhile the alternative hypothesis to random walk model is:

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

The parameter A is a measure of information that is not instantaneously reflected in the prices, meanwhile p measures the speed at which the information is reflected in 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 $R = \text{var}(\mu_t)/\text{var}(\varepsilon_t)$ 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

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

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

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

So, 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 refuse 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:

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

$U_{k,\phi}$ 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

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

3. Parameters estimation and prediction

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 tray to match the theatrical Ap^i and observed r_i autocorrelations, assuming the differences between them is $N(0,\sigma_r^2)$, that is

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

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

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

and n is the sample size of the training period.

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

4. An empirical illustration

In this work the study of the existence of trends is carried out on the main stock markets and index futures markets. Taylor's methodology is applied in four groups of countries' indexes:

- Indexes of developed countries (Dow Jones, S&P500, NASDAQ, FTSE100 of UK, NIKKEI300, DAX30 of Germany, CAC40 of France, MIB30 of Italy, IBEX 35 of Spain, AEX Holland, ASX Australia, JSE of South Africa and Israel asset indexes).
- Indexes of BRIC countries (IBX of Brazil, RTS of Russia, CNX100 of India and China SE Composite Index).
- Indexes of Asian-Pacific countries (Hang Seng Index of Hong Kong, TAIEX Weighted Index of Taiwan, SGX of Singapore, MESDAQ of Malaysia and VNI of Vietnam).
- Index of other developing countries (MXSE of Mexico, IBC of Venezuela, BASE of Argentina, SOFIX of Bulgaria, IGPA of Chile, IGBC of Colombia, CASE30 of Egypt, ISE of Turkey and NSE20 of Kenya).

All series were provided by EcoWin Pro of Reuters. 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 a 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 29-12-2006. The prediction period ranks from 01-01-2007 until 10-18-2007. 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 2, predictions are carried out in the prediction period.

In Table 1 the number of available observations in each asset indexes series and the analysed period is shown.

[TABLE 1]

In Table 2 the results of the U^* test are shown. The test is applied to each asset indexes series from the first observation available in the EcoWin Pro data base (see Table 1) until 29-12-2006. Table 2 also shows 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. As mentioned, all parameters were obtained by maximum likelihood employing a GA.

As a general comment, it is possible to observe in Table 2 that the series where the statistic U^* accepts the trend predominate values of *A* which are less 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. On the contrary, the series where the trend is not accepted have a mean duration of less than 2 days, that is, the new information is incorporated to the prices the same day in which it appears.

With respect to U^* statistic, the results shown in Table 2 point out the following: Of 14 asset indexes of developed countries, 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) in the first six asset indexes of Table 2, that is, Dow Jones, S&P, Nasdaq, FYSE100 UK, Nikkei and DAX of Germany. So, trends are detected in 8 out of 14 countries ($U^* > 1.65$): France, Italy, Spain, Holland, Australia, South Africa, Luxemburg and Israel. However, the mean trend duration is only higher than one day ($m>1$) in the cases of Italy, Holland, Australia and Luxemburg. On the other hand if U^* statistic is applied to the index futures markets in the developed countries, the null of random walk is accepted in all cases. This fact reflects that for the asset indexes CAC40 of France, MIB30 of Italy, IBEX35 of Spain, AEX of Holland, ASX of Australia and JSE of South Africa, its index futures markets are more efficient that the proper spot market. In the case of Luxemburg and Israel the index futures series are not available.

For the BRIC countries the U^* statistic accepts the existence of trends in the case of Russia, with a mean trend duration lower than 2 days, and China, with a mean trend duration of 9 days.

For the Asia-Pacific Securities the U^* statistic accepts the existence of trends for 5 out of 6 asset indexes: Hang Seng of Hong Kong ($m=5$), TAIEX of Taiwan ($m=10$), SGX of Singapore ($m<2$) and VNI of Vietnam ($m=18$). Like before, no index futures markets available accept the existence of trends.

For the group of the rest of emergent markets, the U^* statistic accepts the existence of trends in 7 out of 9 cases, specifically in the IBC of Venezuela ($m=5$), the BASE of Argentina ($m<2$), the SOFIX of Bulgaria ($m=26$), the IGPA of Chile ($m=4$), the IGBC of Colombia ($m=3$), the CASE30 of Egypt ($m<2$), and the NSE20 Kenya ($m=74$). Index futures data is not available in these markets. Finally, Table 2 shows that the U^* statistic accepts the null hypothesis of random walk in the case of MXSE of Mexico and ISE of Turkey asset indexes, revealing a high degree of efficiency in those markets.

[TABLE 2]

5. Economic evaluation of trends: Taylor's strategy

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, 1986) 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

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

where

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

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

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 $\gamma = 0.04$.

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 supposed 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 0.20% 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

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

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 (0.20%), 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).

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 3 reports the values of parameters q, k_1 and k_2 estimated in the training period (from the beginning of each series until 12-29-2006), and the returns, obtained in the prediction period (01-01-2007 until 10-18-2007), 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.

[TABLE 3]

As it is possible to observe in Table 3, in whole asset indexes series where the U^* statistic accepted the null hypothesis of random walk, with a significant level of 5%, the return obtained by B&H strategy is higher than Taylor's strategy. It also happens in all but one of the index futures series. This lack of predictive power is also confirmed by comparing Sharpe's ratios which are lower for the B&H strategy. All of it results in it being very intuitive from the point of view of market efficiency.

The asset indexes presenting a high degree of efficiency (in the sense of not having price trends in the asset indexes) essentially correspond to the group of developed countries, as in the case of the DOW JONES, S&P500 and NASDAQ of USA, the FTSE100 of UK, the NIKKEI of Japan and the DAX30 of Germany. Nevertheless, other developing countries such as Brazil, India, Malaysia, and Turkey have asset indexes showing a high degree of efficiency. The case of Malaysia is exceptional because the U^* statistic accepts the null but the return of the B&H strategy (0.0219) is slightly lower than the return of Taylor's strategy (0.2144).

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

- Countries where, although trend is detected, the trend mean duration is lower than 2 days ($m<2$). This happens in the asset indexes of France, Spain, South Africa, Israel, Russia, Taiwan, Singapore, Mexico, Argentina and Egypt. In this case the trends detected by the U^* statistic have no value in implementing a technical strategy able to beat the market because of their short mean duration.
- Countries where the trends mean duration, higher than 2 days, are detected, but where Taylor's strategy is not able to improve the B&H strategy, neither in

return nor in Sharpe ratios. This is the case with Italy, Holland, Australia, Luxemburg, China and Hong Kong. In these countries although, in theory, the trends detected could be employed to beat the market, in practice it doesn't, 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 2007.

- Countries where the trends mean duration, higher than 2 days, are detected, and where Taylor's strategy overcomes the B&H strategy, as much in returns as in Sharpe ratios. This is the case of Vietnam, Venezuela, Bulgaria, Chile, Colombia and Kenya. These developing country markets were probably inefficient during the years studied and, it was even possible to exploit slight dependence between returns using Taylor's trend model during 2007.

With respect to the capability of obtaining abnormal benefits using Taylor's strategy in the index futures in our prediction period, it is necessary to point out that in all cases, except for the index futures of NIKKEY, Taylor's strategy is incapable of overcoming the B&H strategy and their Sharpe ratios are always lower. So, in the Japanese case, the return obtained by B&H strategy (-0.0394) is lower than Taylor's strategy return (0.0727), in the considered predicting period.

6. Conclusions

In this work we have tested for the random walk hypothesis against the existence of trends in asset index series in the main markets all over the world. With that end, Taylor's (1980) trend price model and Taylor's U^* statistic was employed. 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 assets, was implemented.

Some patterns emerged in our results:

The asset indexes in the most developed countries all over the world presented a high degree of efficiency in the sense of not having price trends in the asset indexes. It happens as much in the asset indexes as in the index futures. Although in several developed countries the U^* statistic reveals the existence of trends, these trends have a mean duration lower than 2 days and are not useful in achieving extraordinary profits.

The BRIC and Asian-Pacific Securities asset indexes are less efficient than those of developed countries because the U^* statistic detects the existence of trends in numerous cases, although the trend mean duration is lower than 2 days and these trends are not capable of producing extraordinary profits when Taylor's strategy is employed.

In most of the rest of the developing countries analyzed, the U^* statistic detects the existence of trends with a mean duration higher than 2 days which may be employed in beating the market, obtaining extraordinary profits. Taking into account that sufficient large and long-life trends in prices will make a market inefficient, our results show that markets in several developing country were probably inefficient during the years studied. So, it may be possible to exploit slight dependence between returns using Taylor's trend model.

No available index futures analyzed presented detectable trend by means of the U^* statistic. It induces the thought that futures markets are more efficient than spot markets. Perhaps this higher efficiency of futures market may be explained by micro structural and institutional friction that presents the spot market which give comparative advantages at futures market, where a speedier and cheaper trading is possible when the generic information arrives [See Stoll and Whaley (1990) and Chan (1992) on the relations between the dynamics of stock index and stock index futures returns].

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Table 1: NAME OF ASSET INDEX SERIES AND ITS FUTURES:	
ASSET INDEXES SERIES	**INDEX FUTURES SERIES**
DEVELOPED COUNTRIES	
United States, **DOW JONES** Averages Composite Index, Price Return, Close, USD (23/12/1980)	United States, Dow Jones, CBT Industrials Futures 1-Pos, Close, USD (06/10/1997)
United States, **S&P 500** Composite, Index, Price Return, Close, USD (01/01/1970)	United States, Standard & Poors, 500 Futures 1-Pos, Close, USD (21/04/1982)
United States, **NASDAQ 100** Index, Close, USD (31/01/1985)	United States, Nasdaq, 100 Futures 1-Pos, Close, USD (10/04/1996)
United Kingdom, **FTSE 100** Index, Price Return, Close, GBP (02/01/1984)	United Kingdom, FTSE, 100 Futures 1-Pos, Close, GBP (03/05/1984)
Japan, **NIKKEI 300** Index, Close, JPY (08/10/1993)	Japan, Nikkei, CME 225 Futures 1-Pos, Close, USD (25/09/1990)
Germany, Deutsche Boerse, **DAX 30** Index, Price Return, Close, EUR (01/10/1996)	Germany, DAX, Futures 1-pos, Close, EUR (28/11/1990)
France, Paris SE, **CAC 40** Index, Price Return, Close, EUR (31/12/1979)	France, Paris SE, CAC 40 Futures 1-pos, Close, EUR (18/08/1988)
Italy, Milan SE, Mta, **MIB 30** Index, Close, EUR (31/12/1992)	Italy, Milan SE, S&P MIB Futures 1-Pos, Close, EUR (08/11/1999)
Spain, **IBEX 35** Index, Price Return, Close, EUR (29/12/1989)	Spain, IBEX, 35 Futures 1-pos, Close, EUR (29/09/1992)
Netherlands, **AEX** Index, Price Return, Close, EUR (02/01/1985)	Netherlands, AEX, Futures 1-Pos, Close, EUR (03/04/2000)
Australia, **ASX**, All Ordinaries Index, Total Return, Close, AUD (31/12/1979)	Australia, S&P/ASX, SPI 200 Futures 1-Pos, Close, AUD (02/05/2000)
South Africa, FTSE/**JSE**, All Share Index, Close, ZAR (01/11/1991)	South Africa, FTSE/JSE, FINI 15 Futures 1-Pos, Close, ZAR (09/02/1999)
Luxembourg, Luxembourg SE, **LuxX** index, Close, EUR (04/01/1999)	Data not available
Israel, Tel Aviv SE, **TA 100** stock index, Close, ILS (03/11/1992)	Data not available
BRIC	
Brazil, Sao Paulo SE, Bovespa Brazil (**IBX**) Index, Close, BRL (05/03/1999)	Data not available
Russia, **RTS**, Index (RTSI), Close, USD (01/09/1995)	Data not available
India, National Stock Exchange of India, **CNX 100** Index, Close, INR (01/01/2003)	Data not available
China, Shenzhen, **SE** Composite Stock index, Close, CNY (04/01/1993)	Data not available
United States, NYSE US 100 Index, Price Return, Close, USD (01/01/1996)	Data not available

(continued)

Table 1: NAME OF ASSET INDEX SERIES AND ITS FUTURES	
ASSET INDEXES SERIES	**INDEX FUTURES SERIES**
ASIA-PACIFIC SECURITIES	
Hong Kong, Hang Seng, **HANG SENG** Index, Price Return, Close, HKD (24/11/1969)	Hong Kong, Hang Seng, Index Futures 1-Pos, Close, HKD (06/05/1986)
Taiwan, **TAIEX** Weighted Index, Close, TWD (05/01/1967)	Taiwan, MSCI, SGX-DT Futures 1-Pos, Close, TWD (17/07/2002)
Singapore, **SGX** Straits Times Index, Close, SGD (04/01/1985)	Singapore, MSCI, SGX-DT Futures 1-Pos, Close, SGD (16/09/1999)
Malaysia, **MESDAQ** Composite Index, Close, MYR (30/04/1999)	Only available until 2006
Vietnam, Ho Chi Minh City SE, VN Index (**VNI**), Close, VND (28/07/2000)	Data not available
EMERGENT COUNTRIES	
Mexico, **MXSE**, IPC General Index, Close, MXN (17/05/1991)	Mexico, MXSE, IPC Index Futures 1-Pos, Close, MXN (12/01/2000)
Venezuela, Bursatil, **IBC** Index, Close, VEB (03/01/1994)	Data not available
Argentina, Buenos Aires SE, General Index, Close, **ARS** (01/12/1993)	Data not available
Bulgaria, Bulgarian SE, **SOFIX** Index, Close, BGN (20/10/2000)	Data not available
Chile, Santiago SE, **IGPA** General Index, Close, CLP (27/09/1993)	Data not available
Colombia, Bogota SE, General (**IGBC**) Index, Close, COP (09/02/1995)	Data not available
Egypt, Cairo SE, **CASE 30** Index, Close, EGP (01/01/1998)	Data not available
Turkey, **ISE** National-100 Index, Close, TRY (04/01/1988)	Data not available
Kenya, Nairobi SE, **NSE 20** index, Close, KES (08/04/1999)	Data not available

Table 2: Taylor's U^* statistics and trend parameters for the asset index series and index futures.
All calculations were carried out from the beginning of the series until 12-29-2006.
The parameters *A* and *p* [*m*=1/(1-*p*)] were obtained through maximizing the logarithm of likelihood function by a genetic algorithm.
N1 is the length of training period and N2 is the length of predicting period.
*Value lower than 1 (each value lower to 2 is round off to 1).

	Asset Index series						Index Futures series					
DEVELOPED COUNTRIES												
	U*	**N1**	**N2**	**A**	**p**	**m**	**U***	**N1**	**N2**	**A**	**p**	**m**
DOW JONES US	-1.1587	6569	200	1.0000	0.0727	1*	-1.2207	2324	203	1.5E-6	2.2E-5	1*
S&P 500 US	-1.7901	9341	202	1.0000	0.0812	1*	-2.5457	6231	203	2.7E-5	9E-7	1*
NASDAQ 100 US	-0.3872	5530	200	1.0000	0.0709	1*	-0.8995	2693	203	0.0010	1.0000	∞
FTSE 100 UK	0.7554	5810	202	1.0000	0.0502	1*	-0.5337	5727	206	0.9011	0.0006	1*
NIKKEI 300 JAPAN	-0.8026	3270	196	1.0000	0.0557	1*	0.7283	4089	209	0.0018	0.9904	104
DAX 30 GERMANY	1.1123	2617	203	0.0056	0.9926	135	0.0464	4060	210	0.0023	1.0000	∞
CAC 40 FRANCE	2.1731	6872	204	1.0000	0.0798	1*	-0.6117	4636	205	0.0013	1.0000	∞
MIB 30 ITALY	2.0422	3545	202	0.0408	0.7962	5	1.1613	1808	210	0.0075	0.9969	323
IBEX 35 SPAIN	2.9018	4268	204	1.0000	0.0699	1*	1.1645	3562	205	0.0039	0.9964	278
AEX NETHERLANDS	3.0967	5584	204	0.0178	0.9480	19	1.0579	1718	211	0.0036	1.0000	∞
ASX AUSTRALIA	5.1952	6858	203	0.0755	0.8178	5	-0.0753	1687	163	0.0020	1.0000	∞
JSE SUTH AFRICA	2.7012	3785	200	0.4358	0.3328	1*	-0.9706	1975	189	6.9E-6	2.3E-5	1*
LuxX LUXEMBOURG	7.3541	2037	201	0.0726	0.9458	18						
TA 100 ISRAEL	2.5226	3467	154	0.1277	0.4265	1*						
BRIC												
IBX BRAZIL	0.9447	1959	199	1.0000	0.0960	1*						
RTS RUSSIA	4.8278	2810	195	0.4207	0.3685	1*						
CNX 100 INDIA	0.4716	993	197	1.0000	0.1174	1*						
SE COMPOSITE INDEX CHINA	2.7256	3501	191	0.0310	0.8939	9						
ASIA-PACIFIC SECURITIES												
HANG SENG HK	7.1088	8906	197	0.0923	0.8011	5	1.6110	5118	202	0.0384	0.7322	4
TAIEX TAIWAN	8.7668	9858	191	0.0518	0.8981	10	-1.2513	1115	191	5.1E-6	2.8E-7	1*
SGX SINGAPORE	4.4635	5507	201	0.3915	0.3850	1*	-1.2513	1115	198	6.9E-6	2.3E-4	1*
MESDAQ MALAYSIA	1.4609	1893	199	0.1592	0.4332	1*						
VNI VIETNAM	13.3288	1499	201	0.1515	0.9451	18						
EMERGENT COUNTRIES												
MXSE MEXICO	1.8188	3892	203	1.0000	0.1258	1*	0.3257	1696	198	1.0000	0.0938	1*
IBC VENEZUELA	7.9555	3192	193	0.1634	0.7951	5						
ARS ARGENTINA	3.5709	3253	197	0.4455	0.2625	1*						
SOFIX BULGARIA	1.6984	1551	217	0.0158	0.9608	26						
IGPA CHILE	14.2579	3310	199	0.3337	0.7612	4						
IGBC COLOMBIA	12.4674	2911	195	0.4703	0.6272	3						
CASE 30 EGYPT	2.8453	2147	161	0.8352	0.2416	1*						
ISE TURKEY	0.2945	4669	201	0.0016	0.9841	63						
NSE 20 KENYA	17.8248	1941	201	0.0860	0.9865	74						

Table 3: Parameters of Taylor's strategy and prediction performance statistics for the asset index series and the index futures for developed countries.
The predictions period ranks from 01-01-2007 until 10-18-2007.
The parameters of Taylor's strategy were obtained through maximizing the Sharpe ratio by a genetic algorithm.

	Asset index series							Index futures series						
	q	k1	k2	B&H	Sharpe B&H	Taylor GA	Sharpe GA	q	k1	k2	B&H	Sharpe B&H	Taylor GA	Sharpe GA
DEVELOPED COUNTRIES														
DOW JONES US	2.46E-7	1.2979	-0.5007	0.0864	0.0458	-0.0711	-0.0387	2.2E-5	1.8977	-0.1082	0.1019	0.0629	-0.0881	-0.0554
S&P 500 US	1.6E-6	0.4706	-0.1014	0.0796	0.0437	-0.4219	-0.2387	9E-7	0.6762	-1.0646	0.0756	0.0415	-0.0283	-0.0159
NASDAQ 100 US	8.5E-7	1.7366	-0.2767	0.2100	0.1020	-0.1412	-0.0723	0.9999	0.9871	-0.0254	0.2134	0.1018	0	0
FTSE 100 UK	3.2E-7	1.0432	-0.4629	0.0525	0.0249	-0.0591	-0.0287	0.0001	0.9065	-0.0733	0.0472	0.0223	-0.1910	-0.0922
NIKKEI 300 JAPAN	3.5E-7	1.3803	-1.1238	-0.0440	-0.0192	-0.1633	-0.0740	0.9888	1.2367	-0.0088	-0.0394	-0.0163	0.0727	0.0315
DAX 30 GERMANY	0.9883	0.3360	-0.1028	0.1483	0.0739	0.0314	0.0161	0.9999	1.7294	-0.0096	0.1667	0.0761	-0.1871	-0.0978
CAC 40 FRANCE	1.06E-7	1.1055	-0.0208	0.0312	0.0145	-0.1482	-0.0710	0.9999	0.8895	-0.0176	0.0192	0.0087	0	0
MIB 30 ITALY	0.7656	0.8241	-0.1237	-0.0350	-0.0182	-0.1727	-0.0924	0.9925	0.0177	-0.0378	-0.0560	-0.0283	-0.1033	-0.0537
IBEX 35 SPAIN	3.1E-7	1.8477	-0.0531	0.0676	0.0313	-0.0659	-0.0313	0.9936	0.8897	-0.0373	0.0744	0.0332	-0.0487	-0.0229
AEX NETHERLANDS	0.9332	1.0165	-0.0116	0.0976	0.0488	-0.1294	-0.0665	0.9999	1.0772	-0.0085	0.0819	0.0395	-0.0917	-0.0471
ASX AUSTRALIA	0.7630	0.2482	-0.0319	0.2085	0.1010	-0.0942	-0.0469	0.9996	1.1177	-0.0144	0.1803	0.0946	-0.1642	-0.0946
JSE SUTH AFRICA	0.1920	1.3050	-0.9384	0.2071	0.0870	-0.2136	-0.0935	2.3E-5	1.0751	-0.1025	0.0717	0.0275	-0.1306	-0.0523
LuxX LUXEMBOURG	0.8969	0.5705	-0.1014	0.1369	0.0662	-0.0375	-0.0187							
TA 100 ISRAEL	0.3733	0.8358	-0.3867	0.1988	0.1143	0.0892	0.0533							
BRIC														
IBX BRAZIL	3.7E-8	0.4770	-0.2026	0.3343	0.1043	-0.3233	-0.1055							
RTS RUSSIA	0.2190	1.3774	-1.3258	0.1782	0.0662	0.2703	0.1074							
CNX 100 INDIA	2.13E-6	0.7579	-0.2325	0.2850	0.0946	-0.1637	-0.0559							
SE COMPOSITE INDEX CHINA	0.8689	1.8483	-0.0359	0.9890	0.2145	0.0077	0.0018							

(continued)

Table 3: Parameters of Taylor's strategy and prediction performance statistics for the asset index series and the index futures for developed countries.
The predictions period ranks from 01-01-2007 until 10-18-2007.
The parameters of Taylor's strategy were obtained through maximizing the Sharpe ratio by a genetic algorithm.

	Asset index series							**Index futures series**						
	q	**k1**	**k2**	**B&H**	**Sharpe B&H**	**Taylor GA**	**Sharpe GA**	**q**	**k1**	**k2**	**B&H**	**Sharpe B&H**	**Taylor GA**	**Sharpe GA**
ASIA-PACIFIC SECURITIES														
HANG SENG	0.7358	0.1264	-0.0863	0.3681	0.1329	0.1888	0.0707	0.7052	1.0341	-0.4140	0.4394	0.1337	0.1912	0.0600
TAIEX TAIWAN	0.8585	0.1847	-0.5489	0.1921	0.0826	0.1844	0.0821	2.8E-7	0.3599	-0.1137	0.1440	0.0471	-0.3367	-0.1144
SGX SINGAPORE	0.2400	1.7958	-0.0301	0.2224	0.0826	-0.2621	-0.1004	2.3E-4	0.3331	-0.1385	0.1682	0.0530	-0.3251	-0.1061
MESDAQ MALAYSIA	0.3662	0.6254	-0.1689	0.0219	0.0059	0.2144	0.0583							
VNI VIETNAM	0.8584	0.2714	-0.1044	0.3663	0.1014	0.4092	0.1282							
EMERGENT COUNTRIES														
MXSE MEXICO	1.0E-6	0.1791	-0.2245	0.2042	0.0799	-0.0387	-0.0158	3.6E-8	1.7022	-0.9007	0.1938	0.0749	-0.0284	-0.0114
IBC VENEZUELA	0.6866	0.4449	-0.4337	-0.3596	-0.0713	0.3843	0.1562							
BASE ARGENTINA	0.1476	0.7793	-0.3788	0.1795	0.0641	-0.0436	-0.0160							
SOFIX BULGARIA	0.9477	0.8839	-0.0620	0.3471	0.1464	0.3955	0.1923							
IGPA CHILE	0.5573	0.9925	-0.6981	0.2182	0.1216	0.2342	0.1342							
IGBC COLOMBIA	0.3688	1.7131	-1.4534	-0.0701	-0.0287	0.0139	0.0065							
CASE 30 EGYPT	0.0415	1.4688	-1.1623	0.2285	0.1166	0.0067	0.0037							
ISE TURKEY	0.9826	1.7450	-0.1823	0.3915	0.1074	-0.6139	-0.1900							
NSE 20 KENYA	0.9490	1.3477	-0.0208	-0.1056	-0.0489	0.0302	0.0146							