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An Investment Strategy Based on Stochastic Unit Root Models

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Abstract

An algorithm is presented that locally approximates the nonlinearity of stochastic unit root (STUR) models by n linear models. The previous integer n is chosen so that the Hadamard matrix of order n can be defined. The strategy $STUR(n)$, then consists in creating n linear models from this Hadamard matrix and taking their average forecast. A purchase (sell) signal is made if the obtained average forecast is positive (negative). Subsequently, a comparison is made with respect to competing models (Moving average strategies) to assess their ability to forecast the variation of five international indexes. It is found, after taking account transaction costs, that $STUR(n)$ generates generally the highest profitability in the out-of-sample data.

Keywords: forecasting, trading rules, random coefficient autoregressive models, efficiency market hypothesis

1. Introduction

The question of Efficiency Market Hypothesis (EMH) has been studied for many years by both academics and market participants. The aim is to see if the assumptions of market frictionless and traders rationality are a good description of real markets where microstructure (transaction costs, information asymmetry, etc.) and noise traders are present. This is an ongoing debate and there has been no consensus. That is why some authors have tried to reconcile the EMH and Behavioral finance arguments through dynamic systems, see for example Lo (2005) and Konté (2010). The empirical studies of this hypothesis are based generally on three classes. The first is *traditional regression models*. Their aim is to test the validity of the EMH in its weak form through traditional time series forecast such as Auto Regressive Moving average models $ARMA(p,q)$. If the market is supposed to be a nonlinear dynamic system, one may consider nonlinear models such as the Random Coefficient Autoregressive RCA(p) or regime switching models among others. The traditional regression models also contain analysis tools based on firms' fundamental (dividend, Book-to-Market, etc.). In this case, the objective is to test the EMH in its semi-strong form (fundamental analysis). We refer to Ou and Penman (1989) and references therein.

The second class uses *Technical Analysis* tools such as Moving Average, Support and Resistance methods. This approach is widely applied by traders to detect trends or reversal effects by using information such that prices, trading volume, etc. Here, the validity of EMH is tested through its weak form, see for example Sullivan et al., (1999).

The last class, based on *Machine Learning* (Genetic Algorithms, Neural Networks methods) investigates the EMH in its weak and semi-strong form as for the class of traditional regression models. Their difference is that Machine learning models are self-adaptive methods in that there are few a priori assumptions about the relationship between inputs while the traditional regression models make strong assumptions (parametric approach).

The paper belongs to the first class where the nonlinearity of financial asset prices is modeled by RCA(p). This econometric model generates the main stylized facts of financial time series, see Yoon (2003). It may be also related to an Agent Based Model with a switching phenomenon between fundamentalists and noise traders, see for example Konté (2011). There are many methods proposed in the literature to estimate its parameters for trading or forecast purpose. For example Nicholls and Quinn (1981) employed the traditional least squares and the maximum likelihood methods, see also Granger and Swanson (1997). Wang and Ghosh (2002) use Bayesian approach while Sollis et al. (2000) work with Kalman filter. We follow here another approach consisting to approximate the $RCA(1)$ model by n simple linear models where n is any integer such that the Hadamard matrix

H of order n can be defined. The latter is an $n \times n$ matrix with all its elements being either −1 or 1, and such that $HH^T=n*I_n$ where H^T is the transpose of H, I_n is the identity matrix of order n. Therefore, the Hadamard matrix columns is an orthogonal binary basis of R^n explaining why it is widely used in physics particularly in the field of signal transmission. The integer n, in this study, must satisfy the constraint n , n/12 or n/20 is a power of 2. The prediction is then made by taking the average forecast of these n linear models extracted from the Hadamatrix since many researchers agree that combining multiple forecasts leads to increased accuracy, see Granger and Ramanathan (1984).

The paper contributes in two ways to the literature. First, contrarily to other forecasting methods, the estimation procedure is made locally to capture traders' feedback or interaction since the variance and other higher moments of STUR model do not exist. Only n data are used in the linear regression models where $8 \leq n \leq 50$. This constraint gives us exactly height (08) strategies $STUR(n)$ with $n \in \{8, 12, 16, 20, 24, 32, 40, 48\}$. The second contribution shows an application of the Hadamard basis to reduce the complexity of a problem (from exponential to linear) for trading purposes.

The paper is divided into four additional sections. Section 2 presents our methodology and its competing strategies to forecast the variation of asset prices of five international indexes (CAC 40, DAX 30, FTSE 100, Nikkei 225, *S&P* 500). Section 3 describes the data and the methodology used in the empirical application. Section 4 presents the empirical results and the last section concludes.

2. Some Forecasting Rules

2.1 Our Methodology

Consider the following stochastic unit root $STUR(1)$ model defined by:

$$y_t = (1+b_t)y_{t-1} + \varepsilon_t \tag{1}$$

$$E(b_t) = E(\varepsilon_t) = 0, \quad E(b_t^2) = \omega^2, \quad E(\varepsilon_t^2) = \sigma^2, \quad \text{cov}(b_t, \varepsilon_t) = 0$$

where (ε_t) is an i.i.d Gaussian process and $y_t=\log S_t$ (log of asset prices).

The properties of eq. (1), to replicate financial times series, have been studied by (Yoon, 2003). The econometric model is also related to an agent based model with interaction between fundamentalist and noise traders, see (Konté, 2011). It is a special case of the Random Coefficient Autoregressive $RCA(1)$ model which is defined by:

$$y_t = (\varphi+b_t)y_{t-1} + \varepsilon_t$$

$$E(b_t) = E(\varepsilon_t) = 0, \quad E(b_t^2) = \omega^2, \quad E(\varepsilon_t^2) = \sigma^2, \quad \text{cov}(b_t, \varepsilon_t) = \psi\omega.$$

(Nicholls and Quinn, 1982) have shown that the RCA(1) process (y_t) is a finite second-order stationary moment if the condition $\varphi^2+\omega^2<1$ is satisfied. Since $\varphi=1$ in our case, the stationary condition is violated (Note 1). That means conventional methods based on this assumption such as Maximum likelihood method cannot perform, see Yoon (2006) (Note 2). Consequently, we propose a methodology that locally approximates the nonlinearity of asset prices by n linear models. For this purpose, b_t is supposed to take only two values α and $-\alpha$ at any time. Therefore, it may be rewritten as $b_t=\alpha X_{t-1}$ where for any t, $X_{t-1}=1$ or $X_{t-1}=-1$. The equation (1) becomes

$$r_t = \log S_t - \log S_{t-1} = y_t - y_{t-1} = c + \alpha X_{t-1} y_{t-1} + \varepsilon_t \tag{2}$$

where a constant c is added, as usual, in the regression model.

For the moment, the estimation cannot be proceed because the variable X_{t-1} is not known. To circumvent this problem, regressions models are used conditional on the path of (X_t). For example, in the equation (2), if it is decided to use n data for the estimation process, we will have 2^n paths for (X_t) , $t=1,\cdots,n$ since X_t takes −1 or 1 at any time. Each trajectory generates a linear model with three input variables X_{t-1}, y_{t-1} and the constant variable c. Therefore, the nonlinearity is approximated by 2^n linear models (Note 3). This feature comes at a cost, as we need to store a binary matrix of size $n \times 2^{n-1}$ to make all linear regressions (Note 4). Generally, we need the parameter n to be big for estimation precisions but not too much to keep a local approximation. In the application, it is taken $8 \leq n \leq 50$. To solve the dimensionality problem, techniques similar to Component Principal

Analysis (CPA) in exploratory data analysis are used. Namely, we extract "*n* orthogonal linear models". Here, the orthogonality of two models *i* and *j* is defined by the orthogonality of their corresponding paths (X^{i}_{t-k}) and (X^{j}_{t-k}), $k=1,\cdots,n$. If *n* is constrained to be an integer such that *n*/2, *n*/12 or *n*/20 is equal to 2^k, $k\in N$, then Hadamard matrices exist. For example for *n*=2, the Hadamard matrix is

$$H_2 = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$$

that is a basis of R^2. Recursively, we can define the matrix H_4, H_8, ⋯, by using the following formula

$$H_{2n} = \begin{bmatrix} H_n & -H_n \\ H_n & H_n \end{bmatrix}$$

This approach allows to pass from exponential (2^n) to linear (n) complexity since now for *n* data used in the equation (2), *n* linear models are also employed where their paths correspond to the columns of the Hadamard matrix of order *n*. For each model, determined by the path of (X_t), the parameters α and *c* are estimated by the Ordinary Least Square method. Then a forecast is made at time *t*+1 through the equation

$$\hat{r}_{t+1} = \hat{y}_{t+1} - y_t = \hat{c} + \hat{\alpha} X_t y_t \tag{3}$$

A recursive regression is applied. At any time, the previous n data are used in the regression model to determine the new estimated parameters. We denote by $SUR(n)$ the strategy that consists to take the average forecasts of all n "orthogonal linear models". The procedure to create the buy and sell signals is then simple: a buy (sell) signal is produced if the average forecast, denoted by $\hat{ra}_{t+1}$, is positive (negative). To reduce the number of transaction costs, we enhance the strategy by allowing static positions in the case where the forecast signal is not significant. In other words, the following strategy is applied for $SUR(n)$.

$$position(t,n) = \begin{cases} sign(\hat{ra}_{t+1}) & if\ |\hat{ra}_{t+1}| > c;\ \ c = (\max(R_t) - \min(R_t))/30 \\ position(t-1,n) & otherwise. \end{cases}$$

where $R_t = \log S_t - \log S_{t-1}$ represents the index return at time *t* (Note 6). The sign function is defined by *sign*(*x*)=1 if *x*>0, *sign*(*x*)=−1 if *x*<0 and *sign*(0)=0.

2.2 Competing Trading Rules

If the market is supposed to be efficient, an optimal strategy is to buy and hold an index. The strategy *B&H* consists therefore to be long on the index at any time and consequently there are no transaction costs. We consider also simple and exponential moving average strategies that have been widely used by traders to capt momentums or reversal effects. The idea is to consider two moving average series *M*(*n*,*t*) and *M*(*m*,*t*) with different lengths *n* and *m*. If we denote by (S_t) the asset price process, the simple and exponential moving average are defined, for a given length *k*>0, by respectively the equations (4) and (5).

$$M(k,t) = \frac{1}{k}\sum_{i=0}^{k-1} S_{t-i} \tag{4}$$

$$M(k,t) = (1-\lambda)M(k,t-1) + \lambda S_t, \quad with \quad M(k,0) = S_1 \tag{5}$$

If *m*<*n* then *M*(*m*,*t*) (resp. *M*(*n*,*t*)) is called the short-term moving average (resp. the long-term moving average). The decision rule for taking positions is specified as follows. If the short-term moving average *M*(*m*,*t*) intersects the long-term moving average *M*(*n*,*t*) from below, a long position is taken. Conversely, if the *M*(*n*,*t*) is intersected from above, a short position is taken. The moving average strategies are implemented by using the Matlab function *movavg*. *Note* that in these strategies, transaction costs appear only when an intersection appears between *M*(*m*,*t*) and *M*(*n*,*t*). In the decision making process of traditional regression models, if a threshold is not used, the number of transactions may be very high.

3. Data and Methodology

In this paper, we consider the daily closing prices of five international indexes *CAC* 40, *Dax* 30, *FTSE* 100, *Nikkei* 225 and *S&P* 500 obtained from *Yahoo Finance* website. All time series have the same length of data as shown by Table 1.

Table 1. Interval of study of the five international indexes

Index	**CAC 40**	**DAX 30**	**FTSE 100**	**NIKKEI 225**	**SP 500**
in-sample	30 Jun 2000	09 Aug 2000	09 May 2000	04 Jan 2000	20 Apr 2000
	19 Feb 2009	13 Feb 2009	30 Jan 2009	25 Dec 2008	30 Jan 2009
out-of-sample	20 Feb 2009	16 Feb 2009	02 Feb 2009	26 Dec 2008	02 Feb 2009
	30 Dec 2011	30 Dec 2011	30 Dec 2011	30 Dec 2011	30 Dec 2011
Total data	2943	2943	2943	2943	2943

All the series end to 30 December 2011, totaling N=2943 trading days. Their difference appears only on the beginning period where the latter is chosen so that to have the same length of data than the Nikkei index.

Each data is after divided into two periods: the first period (in-sample data) contains 2207 (0.75*N) trading days. The remaining data (736 or approximatively 0.25*N) is retained for the second period (out-of-sample data). The use of many geographic zones (Asia, Europa, United States) is to test the robustness of the different algorithms.

The methodology is the following. For each class of trading rules, here *STUR*(n), Simple Moving Average *SMA*(m,n) and Exponential Moving Average *EMA*(m,n), a training period (in-sample data) is used to find its best model in terms of the Sharpe Ratio which is an economic gain adjusted for risk. If we let $R_t=\log S_t-\log S_{t-1}$, the log return of the index at time t, then the Sharpe ratio (SR) is defined for any strategy, say k, by

$$SR(k)=\frac{RM(k)}{\sigma(k)} \tag{6}$$

where

$$\begin{aligned} RM(k) &= \frac{1}{T}\sum_{t=1}^{T} z_t, \quad z_t = position(t,k)\cdot R_{t+1} \\ \sigma(k) &= \left[\frac{1}{T}\sum_{t=1}^{T}\left(z_t - RM(k)\right)^2\right]^{0,5} \end{aligned} \tag{7}$$

Here *position*(t,k) takes 1 (−1) if the strategy k is long (short) at time t and T represents the number of predictions.

The second part consists to compare the performance of the best in-sample models with respect to the out-of-sample data. The comparison is based on many criteria such as the Sharpe Ratio, the winning up periods (W.U.P), the winning down periods (W.D.P), the correct directional changes (C.D.C) and the Maximum Drawdown (M.D). Let $\widetilde{R}_t$ and R_t be respectively the daily trading profit and actual return at time t, $Q_t=1_{\{R_t>0\}}$ and $F_t=1_{\{R_t<0\}}$ the indicator functions for rise and fall at time t, and finally $U_t=1_{\{R_t>0,\,\widetilde{R}_t>0\}}$ and $D_t=1_{\{R_t<0,\,\widetilde{R}_t>0\}}$ the indicator functions for winning up and winning down periods, then the above expressions can be defined by

$$\widetilde{R}_t^c=\sum_{i=1}^{t}\widetilde{R}_i, \quad M.D=\min_{t=1,\cdots,T}\left(\widetilde{R}_t^c-\max_{i=1,\cdots,t}(\widetilde{R}_i^c),\right), \quad C.D.C=\frac{\sum_{t=1}^{T}1_{\{\widetilde{R}_t>0\}}}{T} \tag{8}$$

$$W.U.P=100*\frac{\sum_{t=1}^{T}U_t}{\sum_{t=1}^{T}Q_t}, \quad W.U.D=100*\frac{\sum_{t=1}^{T}D_t}{\sum_{t=1}^{T}F_t} \tag{9}$$

where $\widetilde{R}_t^c=\sum_{i=1}^{t}\widetilde{R}_i$ is the cumulative trading returns up to time t (Note 5).

Finally, we integrate the transaction costs in the analysis. Namely, it is supposed that any transaction implies a constant cost of 20 basis points.

4. Results

We recall that the in-sample data contains approximatively 9 years of data for each index. The *STUR*(*n*) class, with the constraint $8 \leq n \leq 50$ and *n*, *n*/12 or *n*/20 is a power of 2, contains height (08) admissible strategies characterized by the integer *n* valued in {8, 12, 16, 20, 24, 32, 40, 48}. The simple and exponential moving average classes are parametrized by two integers *m* and *n*, representing respectively the lead and lag parameter. In this study, sixteen (16) strategies are proposed for each Moving Average class with their parameters given by $m \in \{1, 5, 10, 15,\}$ and $n \in \{50, 100, 150, 200\}$. All these algorithms need some initial data to start the forecasting procedure. For example, the *STUR*(*n*) strategy needs *n*+1 data to make the first forecast. For these initial data, the agent decision is supposed to be always 1. The cost of one transaction is taken to be 20 basis point i.e 0.2%.

Table 2 shows the performance of the best strategies in each class through the different indexes and through their respective in-sample data given in Table 1.

For the STUR class, the best strategy is given by the parameter *n*=16 for the CAC, NIKKEI and S&P indexes and by *n*=20 and 24 for the *DAX* and FTSE indexes, respectively. Overall, it is seen for the STUR class, the approximation needs to be local or to have less data ($n \leq 24$) to generate good results.

For the Exponential Moving Average class, the lag parameter of the best strategy is always equal to *n*=150 for the different indexes and the lead parameter lies to the set {10, 15}. For the Simple Moving Average class, the lag parameter varies through indexes where the parameter *n*=150 is more frequent. The same remark applies also for the lead parameter m where the mode is given by *m*=15. We also remark that for both moving average classes, a small lead (*m*=1 *or* 5) does not give satisfactory in-sample results. All best competing models (STUR, EMA, SMA), in the in-sample evaluation, generate economic gains or a positive Sharpe Ratio. Furthermore, except in the FTSE index, the optimal strategy of the EMA class outperforms the other best models.

Table 2. Sharpe ratio of the best trading rules in each class (In-sample)

Class	STUR(n)	EMA (m,n)	SMA(m,n)	Buy and Hold
CAC	n=16	m=10, n=150	m=15, n=150	
Sharpe Ratio	0.45	0.741	0.730	-0,37
Dax	n=20	m=15, n=150	m=15, n=150	
Sharpe Ratio	0.627	0.7825	0.5974	-0.218
FTSE	n=24	m=15, n=150	m=15, n=150	
Sharpe Ratio	0.4938	0.451	0.492	-0.210
Nikkei	n=16	m=10, n=150	m=10, n=50	
Ratio	0.222	0.611	0.528	-0.355
S&P	n=16	m=15, n=150	m=15, n=200	
Sharpe Ratio	0.274	0.4728	0.4436	-0.2916

On the other hand, the Buy and Hold Strategy has a negative mean in the in-sample data of all geographical zones showing consequently a negative Sharpe ratio. This may be explained by the fact that all five indexes are highly correlated and therefore the probability to have the same sign performance in the five indexes is very high.

After getting the best strategy in each class, we make a comparison between them. Namely, three trading rules are investigated for each index in their out-of-sample data given in Table 1. The aim is to see if it is possible to do better than the benchmark strategy after taking into account transaction costs. To reduce the chance feature, a long time series of out-of-sample is considered as containing around three years of data. The results are shown in the Table 3 and Table 4 .

Table 3. Out-of-sample performance of the best trading rules in each class (Part I)

CAC	STUR(16)	EMA (10,150)	SMA(15,150)	Buy and Hold
Sharpe Ratio	0.135	-0.72	-0.16	0.125
Transactions	4	20	6	0
M.D	-0.35	-0.83	-0.52	-0.40
DAX 30	STUR(20)	EMA (15,150)	SMA(15,150)	Buy and Hold
Sharpe Ratio	0.53	0.13	0.32	0.40
Transactions	4	4	4	0
M.D	-0.33	-0.42	-0.30	-0.39
FTSE 100	STUR(24)	EMA (15,150)	SMA(15,150)	Buy and Hold
Sharpe Ratio	-0.11	-0.29	0.30	0.49
Transactions	2	10	4	0
M.D	-0.37	-0.34	-0.29	-0.20
Nikkei 225	STUR(16)	EMA (10,150)	SMA(10,150)	Buy and Hold
Sharpe Ratio	0.03	-0.46	-0.77	-0.01
Transactions	3	8	21	0
M.D	-0.32	-0.59	-0.61	-0.33
S&P 500	STUR(16)	EMA (15,150)	SMA(15,200)	Buy and Hold
Sharpe Ratio	0.09	-0.73	-0.20	0.63
Transactions	3	13	4	0
M.D	-0.41	-0.66	-0.40	-0.21

Description: This table presents the out-of-sample values of the Sharpe ratio, the number of transactions and the Maximum Drawdown (M.D) for each best strategy.

Table 4. Out-of-sample performance of the best trading rules in each class (Part II)

CAC 40	STUR(16)	EMA (10,150)	SMA(15,150)
C.D.C	50.41%	47.83%	50.82%
W.U.P	34.32%	52.82%	57.91%
W.D.P	66.94%	42.70%	43.53%
DAX 30	STUR(20)	EMA (15,150)	SMA(15,150)
C.D.C	52.58%	51.90%	51.77%
W.U.P	73.26%	77.12%	76.61%
W.D.P	29.39%	23.63 %	23.92%
FTSE 100	STUR(24)	EMA (15,150)	SMA(15,150)
C.D.C	51.90%	50.27%	50.82%
W.U.P	38.60%	63.73%	60.10 %
W.D.P	66.57%	35.43%	40.57%
Nikkei 225	STUR(16)	EMA (10,150)	SMA(10,150)
C.D.C	51.90%	52.58%	51.36 %
W.U.P	43.16%	48.16 %	51.32%
W.D.P	61.24%	57.30%	51.40%
S&P 500	STUR(16)	EMA (15,150)	SMA(15,200)
C.D.C	50.82%	51.63%	53.53%
W.U.P	46.96 %	66.67%	65.21%
W.D.P	55.69%	32.62%	38.77%

Description: This table presents the out-of-sample values of correct directional change (C.D.C), the winning up periods (W.U.P) and the Winning down periods (W.D.P) for each best strategy.

Table 3 shows that for the Sharpe Ratio criterion, the *STUR* strategy gives overall the best results, namely three over the five indexes. Then it is followed by the *B&H* strategy which performs two times over the five cases. The results of *SMA* and *EMA* trading rules are not satisfactory in the out-of-sample data.

For the Maximum Drawdown (M.D) measure, it is found over all that the two best strategies are also given by the STUR class and the Buy and Hold Strategy (2 over 5 indexes for each). Precisely, the STUR trading rule obtains the good results from the CAC and Nikkei indexes while *B&H* does better in the *FTSE* and *S&P* indexes.

The more *M.D*, the little is the downside risk. The cumulative returns of Figure 1 illustrates both the concept of Maximum downside and profitability (Sharpe Ratio) over the out-of-sample data for the different indexes.

It is noted that the riskiest strategies (downside risk) are usually reached by *SMA* and *EMA* in four among five indexes. For the profitability measure, it is also seen that the STUR and B&H cumulative returns end at the top of the other strategies for the CAC, DAX, Nikkei and S&P indexes. The exception appears only for the FTSE index where *SMA* gives some interesting results.

Now, we are interested in the percentage of correct directional changes (C.D.C), and the percentage of correct directional changes in the rise and fall periods (*W.U.P* and *W.D.P*), see the eqs. (8) and (9) and Table 4.

For the C.D.C criterion, the two best strategies are given by SMA and STUR. The simple moving average trading rule gives better results for the CAC and *S&P* indexes while the STUR strategy performs for DAX and FTSE. The EMA, with a C.D.C of 52.58% only outperforms the other trading rules for the Nikkei index. But, for the *W.U.P* criterion, it is EMA the best trading rules in three over the five indices and then it is followed by *SMA*. However, in financial markets, investors are more concern to detect falling periods. Consequently, the *W.D.P* measure will play a major role for them. It is noted that, for all five indexes, the STUR strategy gives the best results and sometimes the difference is very significant as in the case of CAC and *S&P* indexes.

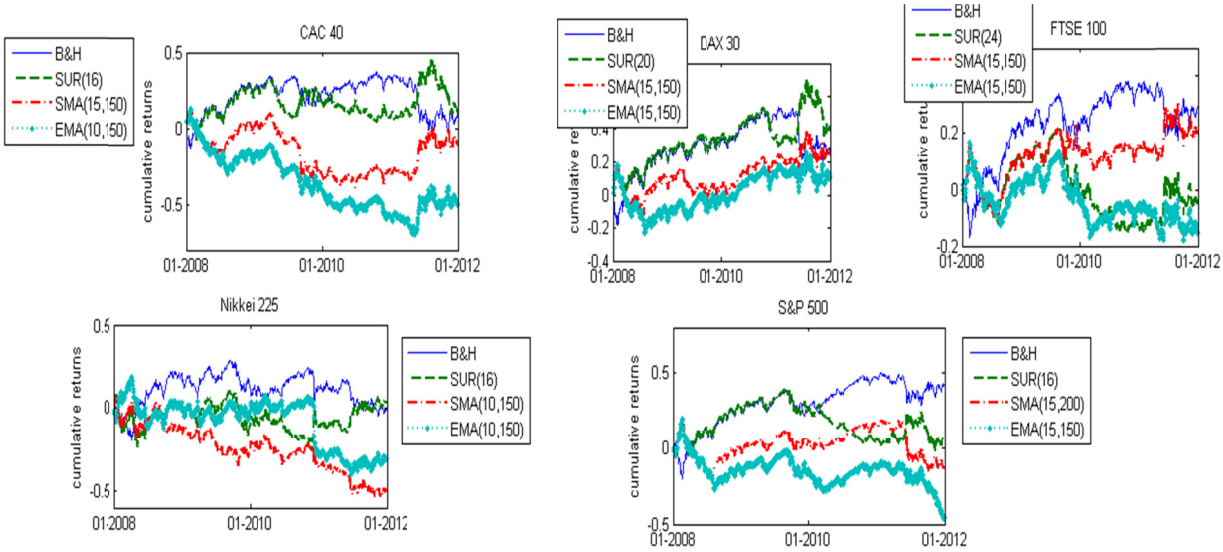

Figure 1. The cumulative return path of the different trading rules for each index

We can resume the analysis, by saying overall, the STUR strategy outperforms the moving average trading rules since it belongs to the best strategies for many criteria such as the Sharpe ratio, the Maximum Drawdown, the Correct directional change and the Winning down periods. Its poor results in the out-of-sample only come from Winning Up period criterion.

5. Conclusion

In this paper, the stochastic unit root model is used to forecast the direction change of asset prices. The contribution consists in approximating locally the nonlinearities of financial time series by simple linear models. For this purpose, two simplifications are made to facilitate the estimation of the parameters. These simplifications are also relevant to reduce the execution time and the memory cost involved by the algorithm. The first is to constraint the stochastic parameter to take, at any time, two possible values. Consequently, for n data used in the regression, the nonlinearities are approximated by 2^n linear models. The second simplification is to solve the dimensionality problem by extracting only the most significant linear models. We follow the idea of the principal component analysis (PCA) by taking n orthogonal binary vectors (columns of Hadamard matrix) of R^n and then associate to each vector, a simple linear model. Then, the strategy *STUR*(n) is defined by taking the average forecast of these n models and the decision making is simply to buy (sell) if this average forecast is positive (negative). To diminish the transaction costs for profitability reasons, but also to capture significant

informations, an endogenous threshold c is used to activate a decision. Namely, the trader will transact if the average forecast return is superior in absolute value to the threshold, elsewhere the previous position is conserved. It is found that the strategies from *STUR* class dominate overall the moving average trading rules (simple and exponential) and also the Buy and Hold strategy for the Sharpe criterion.

These interesting results may be explained by two facts. First, it is known that random coefficient autoregressive models are able to fit well financial asset prices. So it is expected to have satisfactory results when this econometric model is used for forecasting. The second reason is due to our estimation procedure which is local and allows to capture feedback or interaction of traders rather using methods based on stationarity assumptions in variance or higher moments that are violated in our case of stochastic unit root model.

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