RANKING CAPITAL MARKETS EFFICIENCY: THE CASE OF TWENTY EUROPEAN STOCK MARKETS

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Abstract
This study investigates the deviations from efficiency of twenty European Stock Markets using three measures: long-term memory, fractal dimension and efficiency index of Kristoufek and Vosvrda (2012). The markets are ranked according to each measure on a period of fifteen years but also on three sub-periods of time. The sub-periods are chosen depending on the phenomena that has marked the stock market evolution. The results show that the developed markets are closer to efficiency than the emerging ones. Overall, the most efficient markets are the ones of UK, Sweden, Switzerland or France while among the least efficient ones can be mentioned the markets of Bulgaria, Czech Republic, Greece or Slovakia.

Keywords: *capital market, market efficiency, long-range dependence, fractal dimension, efficiency index*

1. Introduction

Market efficiency is one of the most important topics in finance and the subject of numerous studies. The notion itself is abstract and although its simplicity, there is not a straight forward pattern to prove the efficiency or not of a market. An efficient market is assumed to incorporate immediately all the available information and such way, there are no possibilities to earn profits based on past information. Proving that the market does not follow a random walk is not synonymous with market inefficiency, while the reciprocal holds.

In the literature of market efficiency, lots of studies are focused on long-range dependence. If the return series exhibits long-range dependence then the week form of the market efficiency is violated. The presence of long-range dependence or long memory in the return series benefits the technical analysis strategies (Cerqueti and Rotundo, 2014). Based on past informations one can make predictions for future returns. If the dependencies are tracked long time back in the past, the time horizon of the predictions can be larger. Among the first studies of long range dependence are the ones of Mandelbrot and Wallis (1969) or Mandelbrot (1971, 1972) in which was suggested that in the presence of the long memory may exist profit opportunities. Green and Fielitz (1977) identified long memory on 200 daily US stock returns using the rescaled range analysis. The series of papers of Cajueiro and Tabak have used the long-range dependence to rank the efficiency of different markets. Cajueiro and Tabak (2004) ranked the three Asian markets of Hong-Kong, Singapore and China using as measure of the long memory the Hurst exponent, both on the return series and on rolling windows. Same authors (2005) went further and using the rolling sample approach to estimate the Hurst exponent, they ranked the efficiency of the emerging equity markets. It turned out that the Asian countries are more efficient than the ones of Latin America, excepting Mexico. In the article of 2007, when the long-range dependence was searched in the stocks of the Dow Jones Average Industrial Index, the stocks presented an anti-persistent behavior although the Index did not exhibit long memory. Kristoufek (2010) or Ausloos (2012), using for assessing the long range dependence the generalized Hurst exponent proposed by Di Matteo et al. (2003), detrending moving average and detrended fluctuations analysis , contradicts the findings of Serletis and Rosenberg (2009), who found an anti-persistent behavior in the returns of the most important US stock indices by wrong application of the detrended moving average .

On the European stock markets, Cajueiro and Tabak (2006) or Dumitrana *et al*. (2010) or Ausloos (2002) found evidence of long range dependence for all the investigated European stock indices. Moreover, their findings support previous research that the emerging markets present short or long term memory (Rotundo, 2006). Kasman et al (2009) found long memory on the markets of Hungary, Slovakia and Czech Republik but not on the Poland one. Necula and Radu (2012) concluded that the markets of Romania, Hungary, Czech Republik, Poland, Bulgaria, Slovenia, and Croatia exhibit long-range dependence.

Most of the studies have ranked the efficiency of different stock markets based on a specific measure. Kristoufek and Vosvrda (2012) introduced a new measure of the market efficiency based on a combination of several measures. Assuming no correlation structure on an efficient market, the efficiency index incorporates measures of long and short term memory but also of the local herding behavior. When ranking 41 stock markets around the world, the European markets turned out to be the most efficient ones while the markets of Latin America, Asia, Oceania were the least efficient ones. Kristoufek and Vosvrda (2013) utilized a different version of the efficiency index in ranking 38 stock markets. In the composition of the efficiency index were considered the long term memory, fractal dimension and approximate entropy. The analysis revealed that the most efficient markets are the ones of Netherlands, France and Germany while the least efficient ones were the markets of Venezuela and Chile.

Other studies use different efficiency measures to assess the market efficiency. Lagoarde-Segot and Lucey (2006) or Ristea *et al.*, (2010) use an efficiency index based on several statistical tests of the random walk behavior and technical analysis and concluded that in seven emerging Middle-Eastern North African stock markets the weak form efficiency is explained by the differences in stock market size and corporate governance factors. Mensi (2012) used a modified version of the Shannon entropy on a rolling sample approach and a data time window for 100 days together with a symbolic time series analysis to rank the markets and identify the impact of the financial crisis on the level of efficiency. For the 26 analyzed stock markets it was found out that the market efficiency not only changes in time, but is also evolving.

In this study is analyzed the efficiency of twenty European stock markets. These markets are ranked depending on long-range dependence, fractal dimension and the Efficiency Index of Kristoufek and Vosvrda (2012).

The main contribution of this study is that it ranks the efficiency of most of the European stock market indices using three measures of efficiency in which one is an index of several measures. Another contribution is that the rankings were performed not only on a period of fifteen years but also on three sub-periods divided according to the main phenomena that affected the economical, political and social life and implicitly the stock market.

The paper is structured as follows. Second part introduces the methodology and presents the measures that are used in the analysis. In Section 3 is presented the data used. In Section 4 are exposed the results and finally Section 5 concludes the paper.

2. Methodology

In assessing the long-range dependence of the return series are used two approaches. First, the Hurst exponent is computed using the classical R/S analysis and then a rolling sample approach is used to identify if the long-range dependence can be assessed for the entire period of time or if it changes in time. 300 observations are used to create each window and a Hurst exponent is composed for each one. The sample is then rolled one more observation and the first one is dropped. The rolling is stopped when the last sample observation is introduced in the window. In this manner are created several Hurst exponents, specifically the number of observations minus 300, the length of the window. Of course, not all the values of the Hurst exponent can be used in the analysis but instead is chosen the median value. The analyzed indices are ranked according to the median Hurst exponent.

For the fractal dimension are used the Hall-Wood and Genton estimators. The ranking of the indices is based on the average value of the two estimators.

The last ranking of the twenty European stock indices is according to the efficiency index introduced by Kristoufek and Vosvrda (2012):

$$EI = \sqrt{\sum_{i=1}^{n}\left(\frac{\widehat{M_i}-M_i^*}{R_i}\right)^2}, \qquad (1)$$

where $\widehat{M_i}$ is an estimate of the i^{th}measure of efficiency, M_i^* is the expected value of the i^{th} measure in an efficient market and R_i is the range for each measure. For the purpose of the analysis are considered here three measures of the efficiency: the average of Hurst exponent and the median value of the Hurst exponents in rolling windows approach, the average of Hall-Wood and Genton estimator and first order autocorrelation. In an efficient market, the expected value of the Hurst exponent is 0.5 and for the fractal dimension is 1.5. The range is standardized to 1 for Hurst exponent and fractal dimension and 2 for the first order autocorrelation to keep the same maximum deviation for all measures.

In an efficient market EI=0, while in the least efficient market EI=$\frac{\sqrt{n}}{2}$. In our case, with three measures of efficiency, the index of the least efficient market would be 0.86.

2.1. Measure of the long range dependence

The long range dependence measure used is the Hurst exponent. The Hurst exponent is computed using the classical R/S analysis using two different approaches: on the return series and also by means of the rolling sample approach. The return is computed as the difference between natural logarithm of current day closing price and natural logarithm of previous day closing price.

The R/S statistic, as described in Cajueiro and Tabak (2004), is computed as:

$$\left(\frac{R}{S}\right)_\tau = \frac{1}{s_\tau}\left[max_{1\le t\le\tau}\sum_{t=1}^{\tau}(R(t)-\bar{R}) - min_{1\le t\le\tau}\sum_{t=1}^{\tau}(R(t)-\bar{R})\right] \qquad (2)$$

where, $\bar{R}$ is the average return in the considered period

s_τ is the standard deviation estimator, $s_\tau = \sqrt{\frac{1}{\tau}\sum_t (R(t) - \bar{R})^2}$

According to Hurst (1951), the following relation holds:

$$(R/S)_\tau = (\tau/2)^H \tag{3}$$

Hurst exponent takes values between 0 and 1. A value of 0.5 corresponds to a series that does not exhibit long range dependence. Values lower than 0.5 are evidence of long-range dependence with an anti-persistent behavior, while values larger than 0.5 are evidence of long-range dependence with a persistent behavior.

2.2. Measures of the fractal dimension

Fractal dimension is used as a measure of the local memory of the series. The deviations of the short-term trends from a random behavior are captured in the roughness of the series. For a market with no deviations from a random behavior, the fractal dimension measure is expected to be 1.5. Ranging from 1 to 2, a fractal dimension value lower than 1.5 characterizes a series with local persistence while values larger than 1.5 characterizes a rougher series with local anti-persistence.

As measures of fractal dimension, in this study are used the Hall-Wood and Genton estimators, two of the estimators used by Kristoufek and Vosvrda (2012) in computing the efficiency index.

Hall-Wood estimator

As presented by Kristoufek and Vosvrda (2013), the Hall-Wood estimator is given by:

$$\widehat{D_{HW}} = 2 - \frac{\sum_{l=1}^{L}(s_l - \bar{s}) \log \widehat{A(l/n)})}{\sum_{l=1}^{L}(s_l - \bar{s})}, \tag{4}$$

where L≥ 2, $s_l = \log(l/n)$, $\bar{s} = \frac{1}{L}\sum_{l=1}^{L} s_l$ and the absolute deviations between steps are:

$$\widehat{A(l/n)} = \frac{1}{n}\sum_{i=1}^{[n/l]} |x_{\frac{il}{n}} - x_{(i-1)l/n} \tag{5}$$

To minimize the bias, Hall and Wood (1993) suggested L=2, which gives the below estimator:

$$\widehat{D_{HW}} = 2 - \frac{\log A(2/n) - \widehat{\log A(1/n)}}{\log 2}. \tag{6}$$

Genton estimator

This method implies the use of the Genton variogram introduced by Genton (1998) and which is defined as:

$$\widehat{V_2(l/n)} = \frac{1}{2(n-l)}\sum_{i=l}^{n}(x_{i/n} - x_{(i-l)l/n})^2. \tag{7}$$

The Genton estimator is then given by:

$$\widehat{D_G} = 2 - \frac{\sum_{l=1}^{L}(s_l - \bar{s}) \log \widehat{V_2(l/n)})}{2\sum_{l=1}^{L}(s_l - \bar{s})}, \tag{8}$$

where L≥ 2, $s_l = \log(l/n)$, $\bar{s} = \frac{1}{L}\sum_{l=1}^{L} s_l$. For the same purpose as above, L=2 and the Genton estimator is

$$\widehat{D_G} = 2 - \frac{\log \widehat{V_2(2/n)} - \log \widehat{V_2(l/n)}}{2\log 2} \tag{9}$$

3. Data

In this study are comprised twenty indices of the European stock markets that are covering not only the most developed markets but also the emerging ones. Data consists of daily closing prices and was gathered starting 1999 until 2013, with the exception of few indices that were founded later than 1999.

During the analyzed fifteen years, the stock markets went through different behaviors. If between 2003 and 2007 the markets went through constant increases and development, the economical crisis that affected Europe in 2007 has turned the gains into important looses with short periods of slight recoveries. Until the end of 2013 the markets did not manage to recover completely from the effects of the persistent crisis. Due to these important behaviors between 1999 and 2013, the analysis is also performed on the three sub-periods: 1999- 2006, 2007- 2008, 2009- 2013.

4. Results

Table 1 presents the absolute deviations from the expected values in an efficient market of the Hurst exponent and fractal dimension and the values of the efficiency index. All markets exhibit long-range dependence with a persistent character.

The markets of Bulgaria, Slovakia and Greece present the strongest deviations from efficiency if we take a look at the efficiency index, which is also confirmed by large deviations on the Hurst exponent and fractal dimension. On the other side, the most efficient market is the one of UK.

Table 1. Hurst exponent, Fractal dimension and Efficiency Index

Index	Country	Hurst	Fractal dimension	Efficiency Index
ATX	Austria	0.089	0.065	0.116
BEL20	Belgium	0.076	0.02	0.079
CAC40	France	0.038	0.025	0.067
DAX	Germany	0.076	0.045	0.089
OMX	Sweden	0.046	0.125	0.140
SMI	Switzerland	0.060	0	0.065
FTSE100	UK	0.027	0	0.034
GD.AT	Greece	0.118	0.155	0.199
FTSEMIB	Italy	0.072	0.015	0.073
SOFIX	Bulgaria	0.188	0.12	0.231
XU100	Turkey	0.065	0.01	0.067
BUX	Hungary	0.066	0.04	0.081
PX	Czech Republic	0.105	0.02	0.107
SAX	Slovakia	0.109	0.18	0.211
BET	Romania	0.122	0.07	0.148
HEX	Finland	0.074	0.03	0.089
WIG20	Poland	0.085	0	0.086
AEX	Netherlands	0.059	0.005	0.069
OBX	Norway	0.067	0.02	0.070
IBEX	Spain	0.053	0.02	0.068

Figure 1 shows the deviations from efficiency of the analyzed markets for the entire period of time, 1999- 2013. Acording to the median Hurst exponent, the closest to an efficient market is the France market followed by the markets of UK, Sweden and Spain. On the other hand, the least efficient market is the one of Bulgaria. The Romanian, Czech

Republic and Greek markets also present strong deviations from efficiency. It seems that the developed countries exhibit less long-range dependence than the emerging ones. All the indices present a persintent behavior, meaning that the future trend of the index is expected to follow the past behavior. Used as a measure of the local memory of the series, the fractal dimension deviations shown above indicate that the markets of Switzerland, UK and Poland do not exhibit local memory. This indices do not have a local trending behavior. The majority of the indices exhibit negative deviations from an efficient market, suggesting a persistent behavior. The most severe deviations are indentified in the case of Slovakia and Greece.

Applying the efficiency index, the top three efficient markets are UK, Switzerland and Turkey while the markets of Bulgaria, Slovakia and Greece present the highest deviations from an efficient market. It can be noticed that most of the markets have similar, but not high, deviations from the efficiency.

The three measures used to rank the European stock markets for the entire period of time show that the highest deviations from efficiency are presented in the emergent markets, among which are the markets of Bulgaria, Slovakia, Greece, Romania, while the most developed ones present slight deviations from efficiency. The most efficient market seems to be the one of UK, with a low long range dependence and no fractal dimension.

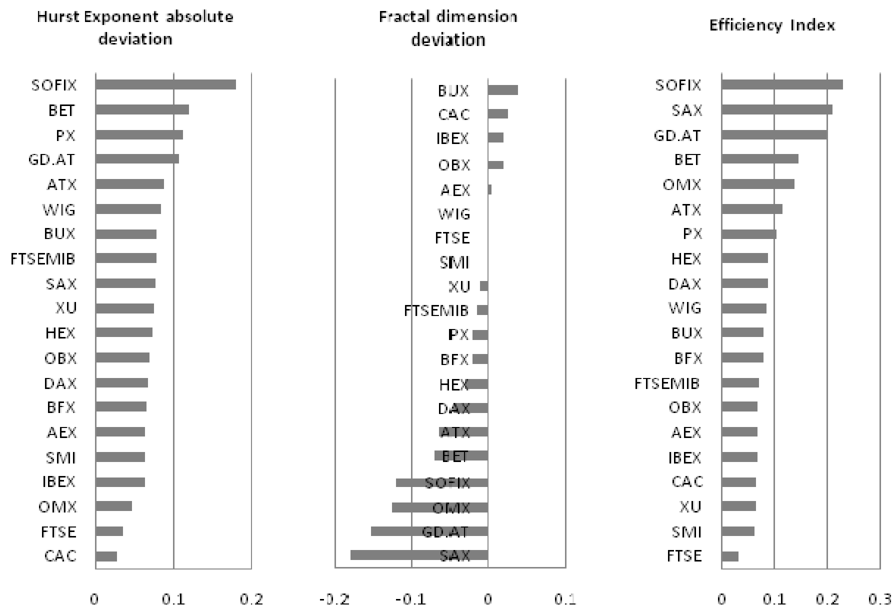

Figure 1. Ranked stock indices according to Hurst Exponent, Fractal dimensionand Efficiency Index between 1999- 2013

Between 1999 and 2006 the stock market has known a period of important increases. Through this period of time, most of the analyzed indices manifest higher deviations from the expected Hurst exponent, as it can be seen in Figure 2. The ranking based on the Hurst exponent is similar to the one of the entire period of time.

The markets of Bulgaria, Slovakia, Greece, Czech Republik or Romania are among the ones that present the strongest deviations from efficiency. The most efficient markets are the ones from UK and France.

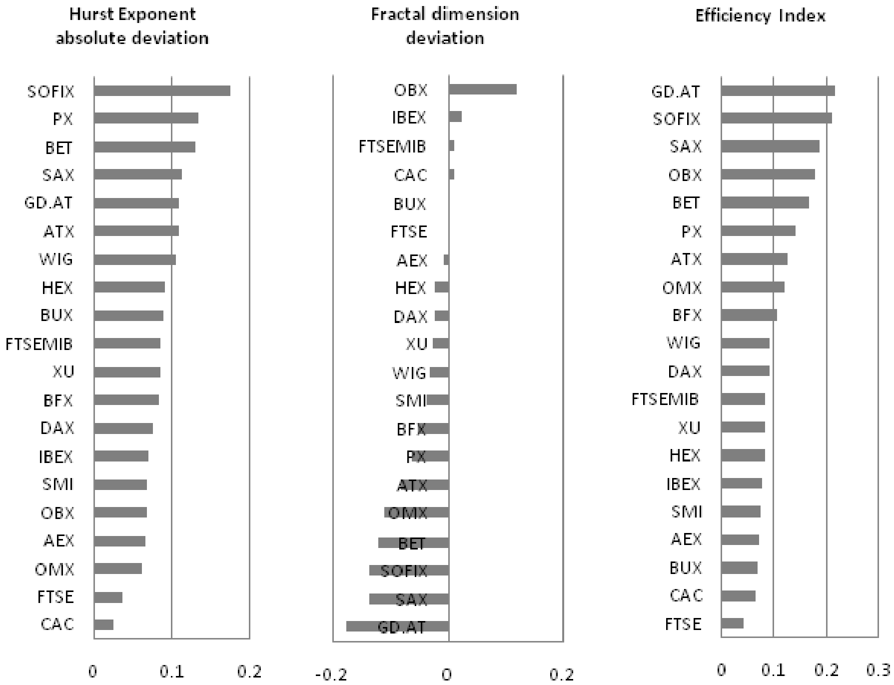

Figure 2. Ranked stock indices according to Hurst Exponent, Fractal dimension and Efficiency Index between 1999- 2006

Characterized by instability, the years of 2007 and 2008 are marked by important looses on the stock market. This behavior is due to the social, political and economical crisis that has affected the entire world. Although the index of France does not exhibit long-range dependence, according to the Efficiency Index, the French market is not efficient. Only the index of Slovakia presents much higher deviations from efficiency, while others, like OMX of the Swedish market describes a more efficient market than in the previous years.

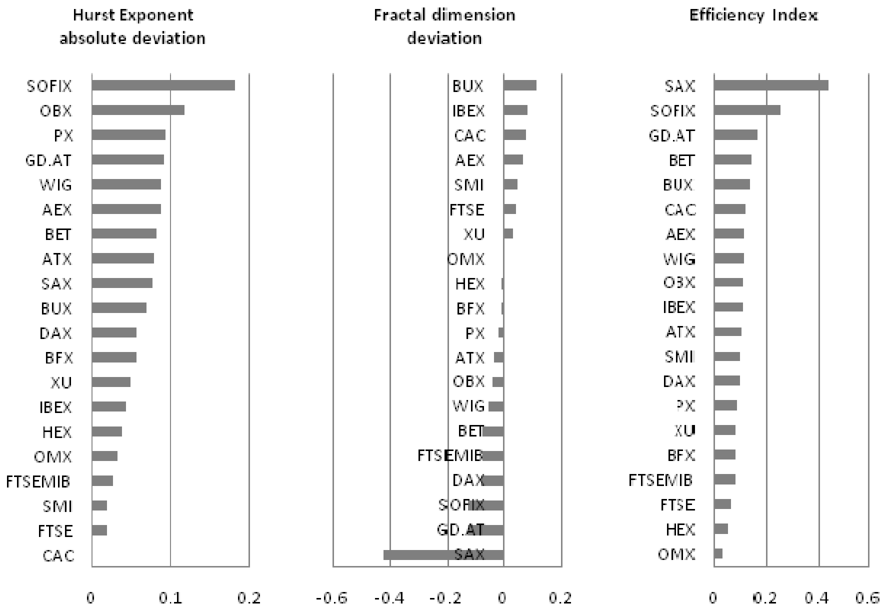

Figure 3. Ranked stock indices according to Hurst Exponent, Fractal dimension and Efficiency Index between 2007-2008

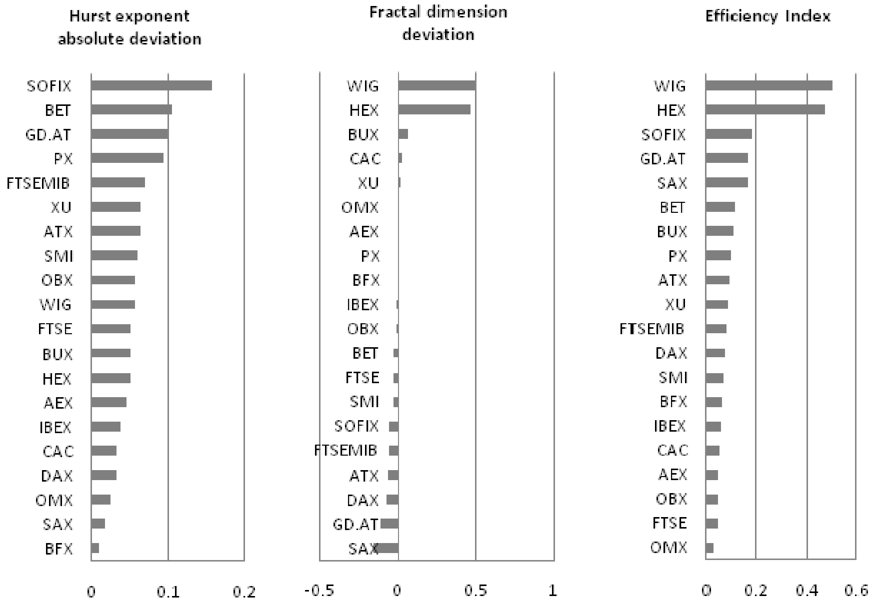

Figure 4. Ranked stock indices according to Hurst Exponent, Fractal dimension and Efficiency Index between 2009-2013

Although the years of 2009-2013 were expected to get the market out of the crash, the expectations din not become reality. The markets presented small deviations from efficiency, with the exception of Finland and Poland, according to the rankings based on fractal dimension and efficiency index, as seen in Figure 4.

In the three sub-periods of time, all markets exhibit long-range dependence, which suggest the predictability of the future returns. The presence of the long-range dependence benefits the technical analysis strategies.

The largest value of the Hurst Exponent was identified for the entire period of time, 0.18 for the index SOFIX of Bulgaria and the smallest value was 0.004 for OMX of Sweden between 2009 and 2013. For fractal dimension, the values covered a larger range, especially between 2007-2008 and 2009-2013, with absolute deviations of 0.495 for WIG of Poland or 0.425 for SAX of Slovakia. In the same time, indices like SMI and FTSE100 do not possess the fractal dimension between 1999 and 2013.

Overall, the indices of the main European stock markets come to support previous findings of Cajueiro and Tabak (2004,2005) or Risso (2008) that the developed markets are more efficient than the emerging ones.

5. Conclusions

Three measures of the market efficiency were used to rank twenty European stock market indices. Long-range memory and fractal dimension were used independetly to rank the markets but also were used as input variables in the Efficiency Index, together with the first order autocorrelation value. The rankings of the three measures were related, showing that the more developed were the markets, the closer were to efficiency. The analysis was performed over a period of fifteen years and also on three sub-periods of time chosen depending on the market behavior.

All the indices present long range dependence, with the exception of the index CAC of France between 2007 and 2008. The markets have a persistent behavior. Looking at the fractal dimension, not all the markets have deviations of the short term trends. Depending on the considered time period, markets like UK, Sweden or Switzerland show zero deviations. As top efficient European stock markets can be mentioned the markets of UK, Sweden, Switzerland or France while among the least efficient ones are the markets of Bulgaria, Czech Republic, Greece or Slovakia.

As further research, the analysis should be extended to other markets and identify the possible causes of the deviations from efficiency and how this benefits the profitability of the technical analysis strategies.

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