Efficient market hypothesis: is the Croatian stock market as (in)efficient as the U.S. market

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Preliminary communication**
JEL: G14
UDC: 336.7

* The authors would like to thank two anonymous referees for their useful comments and suggestions.

** Received: November 28, 2010
Accepted: June 10, 2011

Abstract

Traditional statistical tests of serial independence of stock price changes often show that stock markets are inefficient. Our analysis on daily and monthly data confirms this finding for the Croatian and U.S. markets in the 2002-2010 period. However, this result seems to be mainly due to the impact of the crisis of 2008-2009. The observation of monthly data in the pre-crisis period suggests market efficiency in the U.S. and (rather surprisingly) in Croatia also. Daily data indicate a high degree of efficiency of the US stock market before the crisis, but it is impossible to conclude with a satisfying level of confidence that the Croatian market was inefficient in that period.

Furthermore, an elementary moving average crossover trading system beats the CROBEX and S&P 500 indices from 1997 to 2010, indicating market inefficiency. Still, if the same trading rule is applied to the S&P 500 index in an extended time period between 1950 and 2010, the conclusion about market inefficiency becomes less convincing. It seems that (in)efficiency varies both across markets and in the same markets in the long run, but it still remains unknown which processes are the driving factors behind these changes.

Keywords: efficient market hypothesis, capital markets, CROBEX, S&P 500

1 INTRODUCTION

The main motivation for writing this paper is the lack of research in the area of so-called weak-form stock market efficiency in Croatia. Although the Croatian stock market has existed for twenty years and has developed a solid infrastructure, the very low liquidity still places it in the emerging market category[1]. The first steps in testing its efficiency by measuring autocorrelation of returns started only recently (Barbić, 2010). The objective of this paper is to supplement traditional statistical testing with the assessment of a chosen trading rule (trading system) and compare the results obtained on the Croatian market with findings on a more developed equity market (U.S.). We used the same methodology in testing for so-called weak-form statistical and trading efficiency on these two markets and found similar results: a surprisingly similar efficiency before the recent crisis and a somewhat less surprising inefficiency in the aftermath of the collapse of Lehman Brothers. The analysis also revealed trading inefficiency, as it proved to be easy to find a trading rule that beat the market.

A similar in(efficiency) in capital markets as different as those in Croatia and the U.S. is not a puzzle if one takes into account a number of problems related with the design of empirical tests and interpretation of their results. The common denominator of numerous formulations of the Efficient Market Hypothesis (EMH) is the idea that investors cannot beat the market in the long run. The market is considered efficient if participants using all available information (including past pri-

[1] Annual stock market turnover to GDP ratio is consistently below 7%.

ce changes) cannot create strategies that consistently beat the average market returns. Many papers testing this main postulate of the EMH have been published. The usual procedure is to test for serial independence of stock price changes. Statistical serial independence of price changes (zero autocorrelation) implies that it is not possible to forecast future price changes using observed past prices changes. In this case, prices follow a "random walk" pattern – today's changes have no influence on tomorrow's price changes. However it remains puzzling whether some degree of statistical predictability of future on the basis of past returns is enough for investors (at least for "sophisticated traders") to be able to exploit this information profitably.

Formulation of the weak-form market efficiency condition based on the random walk model was dominant in economic thought until the 60s. However, Samuelson (1965) and Mandelbrot (1966) showed that price behavior associated with the martingale model rather than the random walk model is a better description of asset price movements in an informationally efficient market. An implication of the martingale model is that a market can be efficient even if there is correlation of successive price changes under the assumption that economic agents are risk averse (LeRoy, 1989). The same implication follows from the rational expectations formulation of efficient market theory (LeRoy, 1973; Lucas, 1978). Also, one should not be surprised to detect serial correlation of changes in prices of financial instruments in informationally efficient markets when there are large changes in exogenous variables such as income, wealth and/or attitudes towards risk.[2] However, the finding of serial independence of price changes is still an indication of market efficiency.

Therefore statistical tests in the random walk tradition have weak theoretical foundations and are of dubious importance for market participants. No wonder that statisticians as well as some economists on one hand, and investors on the other, do not perceive market (in)efficiency in the same way. For a market practitioner inefficiency is the existence of a winning trading system that consistently generates profits above the benchmark, which represents the market. However, there are weak theoretical foundations for this type of test, too.

Filter rules/mechanical trading systems are precise instructions about when to buy or sell a financial instrument with the goal of achieving above-average profits. Tests of filter rules/mechanical trading systems have been performed for decades with varying successes (in terms of "beating" market indices). Interpretations of their results have varied even more than the results themselves. Some authors (e.g. Fama, 1965; Fama and Blume, 1966) interpreted the impossibility of beating the market in favor of the EMH, although they did not discuss how many trading rules are possible or the significance of finding a rule or several rules that did not beat the market. Similarly, the discovery of a rule/trading system that beats the market

[2] See Le Roy (1989) for a useful survey of the literature.

average has no clear cut theoretical interpretation in terms of market (in)efficiency as it is not clear how probable it is to find such a rule by chance. Notwithstanding theoretical problems, such a finding catches the attention of stock traders.

Given the theoretical limits described above, this paper provides a substantial body of descriptive statistical evidence about the functioning of the Croatian stock market (Zagreb Stock Exchange) in the period 1997-2010. Descriptive evidence is organized and interpreted within the theoretical tradition of market efficiency. Given the numerous ambiguities that are present within this tradition[3] we urge readers to interpret the results critically. We hope we have provided guidance regarding caution in the interpretation of results throughout the paper.

The paper is divided into six sections. After the introduction, the second part gives an overview of the literature related to traditional market efficiency testing, as well as research done on the effectiveness of various trading systems/filter rules. In the third section, data and methodology are described. The fourth section presents and interprets the results. The fifth section discusses the problems with interpreting the results. Concluding remarks are found in the final section.

2 LITERATURE OVERVIEW

Fama (1965) tested for serial independence of Dow Jones Industrial Average (DJIA) component price changes. He concluded that markets are efficient, with prices behaving like a "random walk" although the distribution of price changes was not gaussian. Numerous researchers built upon his work. Earlier studies supported Fama's proposition, but most of the work conducted later, especially in the 80s on developed and emerging markets, questioned the serial independence of price changes. For example, Poterba and Summers (1988) examined the U.S. and seventeen other developed markets and found that returns were positively correlated in the short-term and negatively correlated in the long-term. This was backed up by Fama and French (1988) who found negative serial correlation of long-term returns. Lo and MacKinlay (1988) detected positive serial correlation of short-term price changes (less than one year).

Although the outcome of these studies points to the presence of short-term trends and long-term mean-reversion in the stock markets, this ultimately did not lead to the formulation of usable trading strategies. A hint as to this was given by Jegadeesh and Titman (1993) who concluded that stocks that had outperformed the market in the past 3 to 12 months tended to outperform the market in the following 3 to 12 months. While the performance of individual stocks remains highly unpredictable, the authors state that the market can be beaten by constructing *portfolios* of the best performing stocks in the recent past. Pesaran and Timmermann (1995) also observed return predictability that changes with time – it is higher in eco-

[3] LeRoy (1989) also provides for a thorough review of these ambiguities.

nomically volatile periods (like the 1970s) and significantly lower in economically relatively calm decades (like the 1960s and 1980s).[4]

Similar outcomes were observed while testing emerging markets. Harvey (1994) and Claessens et al. (1995) conclude that emerging markets (with a heavy weighting of South American and Asian emerging markets) show significant serial correlations of returns, indicating that serial correlation may indeed have some value as an indicator of market (in)efficiency. Earlier studies of the new European emerging markets showed the inefficiency of the Polish stock market in the first half of the 1990s (Nivet, 1997), which was in contrast with findings for the Hungarian market. According to Chun (2000), it exhibited no predictability of returns although it was in its infancy in the 1990s. Mateus (2004) notices high serial correlation of returns on stock markets of the 13 new EU accession countries. Comparable findings came from Cajueiro and Tabak (2006), who observed short- and long-term predictability of returns on European transition markets. Barbić (2010) investigated the Croatian market and found some statistically significant but unstable autocorrelation coefficients with low values that are hardly associated with meaningful trading strategies.

Simultaneously with testing for autocorrelation, academics and market practitioners tested the EMH by comparing the *buy and hold* strategy (which supposedly produces average market return) with filter rules/mechanical trading systems.[5] The most popular mechanical trading systems are breakout and moving average crossover systems. One simple example of a breakout system is “buy when the price of a security breaks above its 10-day high and sell when the price falls 2% below its subsequent high”. Moving average crossover systems are based on the assumption that when a short-term moving average (MA) crosses a longer-term MA from below one should buy because a new uptrend is about to be formed. The opposite should be done when the shorter MA crosses the longer from above, since a new downtrend is likely to emerge.

The main premise here is that if mechanical trading systems were consistently to outperform the market index, then market efficiency could be challenged. Alexander (1961), Fama (1965), and Fama and Blume (1966) tested filter rules on the U.S. market and found that they cannot generate above-average trading profits. Van Horne and Parker (1967) chose 30 U.S. stocks at random and bought and sold them based on their price crossing the 200-, 150- and 100-day moving average. They found that none of the price-moving average combinations resulted in profits that could not be achieved by the simple *buy and hold* strategy.

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[4] Drifts in predictability are associated with different market regimes in bull (high return-low volatility) and bear (low return-high volatility) markets. It is very well documented that all correlations tend to increase in bear market regimes. See Kunovac (2011) for a useful review of the literature and results for the Croatian market.

[5] Statistical tests of autocorrelation and the tests of trading rules/systems are not the only tests of EMH. Many event studies indicating violations of EMH gave birth to an astonishingly wide field of behavioural finance. A reader should look for surveys of behavioural finance elsewhere in the literature (e.g. Shefrin, 2002).

More recent studies give a different picture, though. Brock et al. (1992) tested various breakout and moving average crossovers systems on the DJIA from 1897 to 1986. They stated the superiority of technical trading systems over the *buy and hold* strategy. Buy and sell signals consistently generated returns higher than "normal" results. Kwon and Kish (2002) support the Brock et al. study using a sample of broader market-cap weighted indices like the NYSE and NASDAQ. They found that technical trading rules added value by capturing profit opportunities when compared to a *buy and hold* strategy. Siegel's findings (2002) are also intriguing: investment based on a long-term trading rule beat the NASDAQ Composite, and fared only slightly worse than the DJIA (but with significantly lower risk).

Fifield et al. (2008) examined moving average rules for 15 emerging and 3 developed markets over the period of 1989-2003. Their results indicate that the return behavior of emerging markets differed markedly from that of their developed market counterparts; moving average rules were more profitable when tested using emerging stock market indices. In addition, this profitability persisted for longer moving averages, suggesting that trends in stock returns were larger and more persistent in emerging markets. Jagric et al. (2005) tested five Central European markets (Slovenia, Hungary, Poland, Slovakia and the Czech Republic) and Russia on the effect the transition process had on the market efficiency. They tested these markets with a technical trading system comprised of an MA crossover system (15-50 days) for trending periods and the Relative Strength Index (RSI) for sideways periods.[6] With the exception of Slovakia and Poland the mechanical trading system outperformed the *buy and hold strategy*.

The brief literature review presented here comprises only a small fraction of literarily hundreds of relevant studies, the sheer number ensuring that any attempt at comprehensiveness would be certain to fail. Instead, the main purpose of this review is to illustrate the diversity of the empirical findings, which provide very few priors. This is hardly a surprise given the fact that theoretical underpinnings of informationally efficient markets and their statistical tests are vague. In this respect, tests of serial correlations of price changes can be interpreted as efficiency tests only under very restrictive conditions of random walk in stock prices, which is not considered to be a valid theory of asset price movements. Moreover, it implies risk neutrality and no significant changes in exogenous variables such as income, wealth or risk-appetite, not to mention technological changes. For that reason, finding serial dependence does not lead to rejection of EMH. However, finding serial independence is an indication of efficiency. Similarly, mechanical trading systems may be very interesting for market practitioners but there is no clear theoretical pathway showing how to interpret the implications of their results on market efficiency. Readers should bear this in mind while interpreting our results.

[6] The relative strength index (RSI) measures the relative strength of price changes when prices go up vs. price changes when prices go down. It is considered to be a technical measure of momentum. Its maximum value equals 100, which is reached when exponential moving average of downward changes in prices equals zero.

3 METHODOLOGY AND DATA

Our test of market efficiency of the Croatian stock market (Zagreb Stock Exchange – ZSE) rests on two pillars. The first part of our market efficiency test is the statistical test of autocorrelation. The second part is an attempt to find a simple trading rule that would exceed returns of the stock index in the long run. We compared ZSE and NYSE with the use of both approaches.

3.1 STATISTICAL TEST OF AUTOCORRELATION OF RETURNS

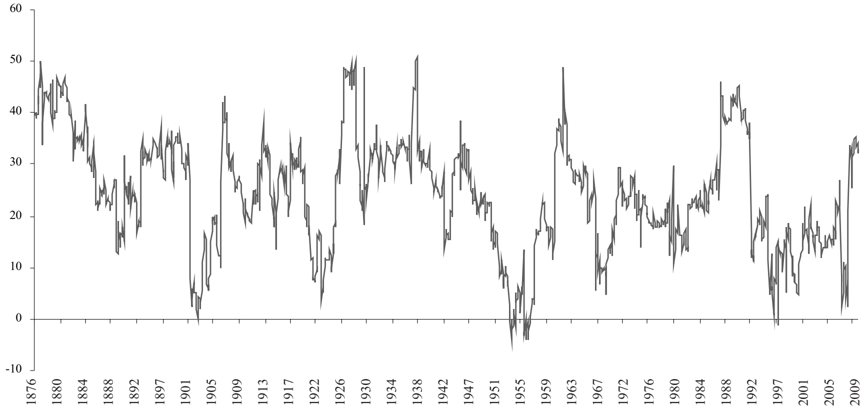
For Croatia, the analysis was based on official stock index data of the Zagreb Stock Exchange (CROBEX) from 2 January 1997 to 2 June 2010. Of interest here is the autocorrelation of changes in the value of the CROBEX market index. The analytical technique used in Lo (2004:23) was used to compare results for Croatia and the U.S. Lo's (2004) data for the U.S. comprise 133 years of monthly returns on the S&P 500 in the period from 1871 to 2003. He shows successive autocorrelation coefficients of investment returns on the U.S. stock exchange index Standard & Poor's (S&P 500) by fixing the sample size to 60 months and successively moves ("rolls") the time sample towards the last – most recent monthly observation. As this is a 60-month forward moving sample, the first observation of autocorrelation is in the 61st month following the first observation in the sample. Lo (2004) computed and plotted the first-order autocorrelation for each sample. Based on the changes in autocorrelation coefficients for successive time periods he obtains a time series showing a "degree" of market efficiency: the market is "less efficient" if autocorrelation coefficients move further away from zero and vice versa.

Here we created a replica of Lo's (2004) results on the sample of data from 1876 to 2010, using Robert Shiller's (2010) database (figure 1). One sees a relatively high average autocorrelation of returns, ranging from 20% to 30%. Lo (2004) used this result to support the conclusion that the U.S. capital market is inefficient. Also, strong variations of the autocorrelation coefficient across time support his belief that market (in)efficiency drastically changes over time. Lo (2004) considers that in more recent times market efficiency quickly decreases (autocorrelation increases) after reaching efficiency peak in 1997, as confirmed by the data from the replica in figure 1 up to 2010. Large autocorrelation variations in the long run confirm the idea developed in the adaptive market hypothesis (AMH)[7] tradition that structural changes appear in the market over long-term periods that may be related to changes in psychological characteristics of market participants (risk aversion), regulation, institutional infrastructure, wealth, technology, etc.

[7] The adaptive market hypothesis, as proposed by Andrew Lo (2004, 2005), is an attempt to reconcile theories that imply that the markets are efficient with behavioral alternatives, by applying the principles of evolution – competition, adaptation, and natural selection – to financial interactions.

Figure 1

Autocorrelation coefficient of monthly returns on the S&P 500 index on the 60-month moving time sample from 1876 to 2010 (%)



Sources: Lo (2004), Shiller (2010) and authors' calculations.

It is of critical importance to distinguish "noise" from significant variability of autocorrelation. It may be that only the most extreme upper and lower observations have some significance. For that purpose, critical values for the two-sided test of statistical significance of linear correlation coefficients are calculated by the following formula:

$$0 \pm z_{\alpha/2} \frac{1}{\sqrt{N}} \tag{1}$$

where N is the sample size, i.e. the number of observations in the period observed. If the absolute value of the correlation coefficient exceeds the critical value, the autocorrelation is different from zero at the given significance level.

In figure 1 above, the following four periods of efficiency would be of interest at a statistical significance level of 1%[8]: (a) the very beginning of the 20th century; (b) early 1920s; (c) mid-1950s; and (d) late 1990s. Also of interest would be the following inefficiency peaks: (a) the time of the 1907 crisis and WWI; (b) before and after the Great Depression; (c) early 1960s; and (d) late 1980s and early 1990s.[9] The recent market situation also indicates inefficiency.

The first observation for Croatia is in January 1997, so the calculation of autocorrelations begins 60 months later. One month is lost due to calculation of monthly changes and another one due to the shift of the first order, so the relevant time period is March 2002 – May 2010, i.e. 98 monthly observations. The end of the month observation is taken as the data for that month.

[8] Critical value at 5% significance level of the two-sided test is 25.3%.
[9] Even a cursory look indicates the fact that inefficiency peaks are somehow linked to crises.

As far as daily data is concerned, in the period from 2 January 1997 to 2 June 2010, there were 3,335 trading days on the Zagreb Stock Exchange. In the same period, there were 3,466 trading days on the New York Stock Exchange. This difference in the sample size (3.9%) has no significant bearing on the results. The first 5-year sample (1,236 trading days) of daily data for Croatia comprises changes in the CROBEX from 3 January 1997 to 3 January 2002. We observed the correlation between daily changes over that time sample and daily changes in the period of the same duration moved forward by one day. Moving the time period of the same duration day by day until the last observation on 2 June 2010 ("rolling") provides a sequence of 2,100 autocorrelation coefficients for one-day lagged 2,100 sub-periods, i.e. time samples from 4 January 2002 to 2 June 2010. The percentage of 2,100 coefficients that exceeds critical values was observed. Critical values for the time sample of 1,236 observations are 7.3% at a significance level of 1% and 5.6% at a significance level of 5% of the two-sided test.

3.2 FILTER TEST / MECHANICAL TRADING SYSTEM

Moving averages are among the most popular technical analysis tools. Due to differences in the number of days entered in the calculation, there are in theory as many moving averages as there are investors. Still, *stockcharts.com* highlights the most popular ones: 5-20-day averages are most often used to present short-term market trends, 50-day averages are used for medium-term trends and 200-day moving averages are used to determine long-term trends.

In addition to simple moving averages in which all prices have the same weight, market participants use the exponential moving average (EMA):

$$EMA_t = P_t K + EMA_{t-1}(1 - K) \tag{2}$$

where P_t is today's price, N is the number of days for which the exponential moving average is calculated and K is the weight of the most recent observation:

$$K = 2/(N + 1) \tag{3}$$

The most recent price, which enters the calculation last, has the greatest weight in calculation of averages, while the oldest price has the least weight. This is why EMA reflects the current situation in the market more objectively than simple moving averages where the oldest and the most recent price receive the same weight. So far, it has not been proved beyond doubt that the use of exponential moving averages is more profitable that the use of simple averages. Still, the more logical assumption that more recent prices are more relevant in securities trading than older prices prevailed in the selection of the method. This is the main reason why exponential moving averages are used.

There are several basic ways of using moving averages for the purpose of securities trading (Murphy, 1999): (a) buy when the price exceeds the chosen moving average, and sell when its price falls below the moving average; (b) buy when the chosen moving average turns up, and sell when the chosen moving average turns down (Elder, 2002); and (c) buy when the shorter moving average (e.g. 20-day) crosses above the longer moving average (e.g. 50-day), and sell when the shorter moving average crosses below the longer moving average (moving averages crossing). The time horizon of an investment based on moving averages depends on the chosen length of moving averages: the shorter the moving averages, the shorter expected period of investment, and vice versa. For example, a trading based on the crossover of the 10-day moving average generates a signal to buy/sell every few days, while the approach applied to a 200-day moving average results in only several transactions a year. The CROBEX and S&P 500 were tested using the moving average crossover strategy, where the 50-day EMA was taken as the shorter moving average and the 200-day EMA was used as the long-term moving average (50/200 EMA). The moving averages were selected with the intent to create a trading system that will rarely give signals to buy/sell and thus keep an investor within the prevalent trend for as long as possible. This combination, while generally accepted among market participants and often used in determining long-term trends in the market (Carr, 2008) is not prominently covered in the listed academic research.

The simulations were run by using MetaStock version 10.1 (Equis International) software. The testing period begins on 2 September 1997 and ends on 2 September 2010 (a total of 3,250 trading days). Initial capital is 100,000 monetary units (mu). The trading system manages the funds according to the following rules: (a) when the 50-day moving average crosses above the 200-day moving average, total capital is invested in the CROBEX at the opening price on the first day after the crossing (if the opening price is not available in the system, the closing price on the first day after the crossing is used); (b) when the 50-day moving average crosses below the 200-day moving average, the whole position is sold at the opening price on the first day after the crossing (if the opening price is not available in the system, the closing price on the first day after the crossing is used); (c) purchase and sale transaction costs are equal to 1% of the current portfolio value; (d) in periods when not invested in the market, the investor earns an average annual rate of 3% on cash. The trading system allows only for the entire portfolio to be exposed to equity risk or the entire portfolio to be returned to the neutral position (cash). Real strategies can be much more complex. For example, a partial portfolio exposure to stocks and partial holding of cash is possible. Such strategies are not analyzed as they cannot provide a clear picture of superiority over the market average. Also, it is possible to exclude a neutral cash position and analyze the strategy of continuous two sided exposure to equity. This strategy is subject to errors in both directions and yields a much poorer result than the neutral position strategy.

Although the period of the last 14 years represents a "large sample" in statistical terms, when concluding on the validity of trading rules the size of the sample cannot be defined by the same method as one would decide on the sample size to conclude on probabilities in coin tossing or another phenomenon whose "drawings" are random. In this case it is known that the nature of serial dependence varies across time. This means that longer historical periods may have unique characteristics, which market participants have to learn during the periods themselves. These structural characteristics of the market change from time to time, thereby changing the rules of the game. Learning then starts from the beginning. In this light, a hypothesis may be proposed that the rule will find it much harder (if at all) to beat the market over an extended period of time since that time framework includes structurally different periods during which there are learning cycles and the winning strategies change. This is why the S&P 500 index was used to test the moving average crossover system in the period from 3 January 1950 to 2 September 2010 (a total of 15,266 trading days).

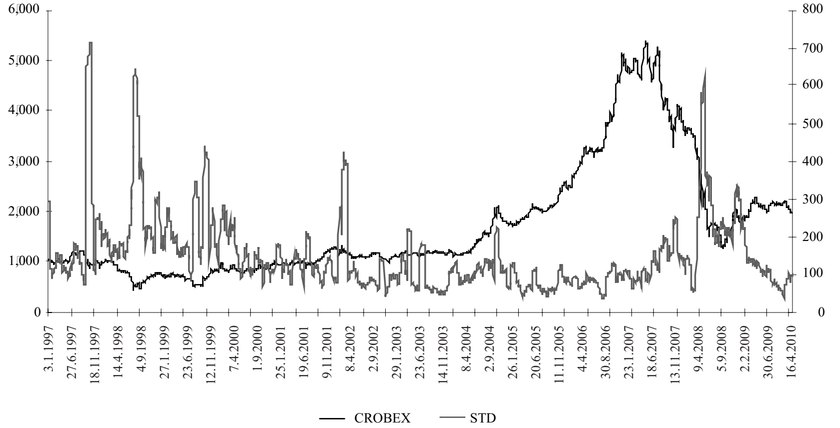
4 RESULTS: CROATIA AND THE U.S.

4.1 STATISTICAL TEST OF AUTOCORRELATION OF SUCCESSIVE PRICE CHANGES

The CROBEX index and the moving 20-day standard deviation of its daily changes are shown in figure 2. It is evident that the 1990s were extremely volatile, with much larger swings than in the first decade of the 21st century, which was marked by a very tranquil period of index growth up to 2007. At that time, fluctuations began to increase, and the crisis escalated with the collapse of Lehman Brothers (September 2008). Then the variance of price changes decreased again as index begun to rise.

FIGURE 2

CROBEX index (left scale) and the measure of its volatility (right scale, %) in the period from 2 January 1997 to 2 June 2010



Sources: Zagreb Stock Exchange (2010) and authors' calculations.

Figure 3 shows autocorrelation coefficients of monthly returns on the CROBEX and S&P 500 indexes on the 60-month moving monthly time samples from March 2002 to May 2010. This figure compares a replica of Lo's (2004) results shown in figure 1 with time series of successive autocorrelation coefficients obtained on CROBEX.

CROBEX had a lower average autocorrelation of successive monthly price changes than S&P 500 from March 2002 to May 2010. Similarity of changes in autocorrelation patterns from 2007 to 2010 is striking. First, autocorrelation coefficients were approaching zero in both markets in late 2007/early 2008. Then there was a sharp coordinated increase associated with the collapse of Lehman Brothers in September 2008. Autocorrelations subsequently remained at elevated levels in both markets. Coefficients are not statistically different from zero at 5% significance level until 2007.[10] Then U.S. market becomes inefficient (statistically significant positive serial correlation of price changes) for a very short period in 2007 (see the local peak in 2007) and then both markets became inefficient after Lehman Brothers collapse as coefficients rose at about 30%. It is striking that two such different markets produce such similar time series of autocorrelation coefficients at monthly frequencies:[11] the linear correlation coefficient of time series of autocorrelation coefficients in Croatia and the U.S. for the 2002-2010 period stands at a very high 73.6% for monthly price changes.

The result indicating large similarities in (in)efficiency of two extremely different capital markets may be considered a puzzle. The usual assumption is that the U.S. market, which is several thousand times more liquid than the Croatian market (not to mention the longevity, institutional structure and experience of participants), should be much more efficient. Numerous empirical studies of both developing and developed countries confirmed such a relationship, the literature mainly discussing whether a lower degree of institutional development and liquidity (i.e. higher market risk in developing countries) may account for a higher return on investment in stocks listed on these markets (Barbić, 2010).

On the other hand, if one remembers that Lo (2004) was also surprised by the fact that the New York Stock Exchange today may not be as efficient as in some periods 15, 50, 100 and even more years ago, the result of the comparison between Croatia and the U.S. should not come as a surprise. There are market processes in force that in the long run considerably change the statistical characteristics of stock price time series. These processes also significantly change the relationship between efficiency of different markets – regardless of the degree of their development. Unfortunately, which processes are in force and how they create changes

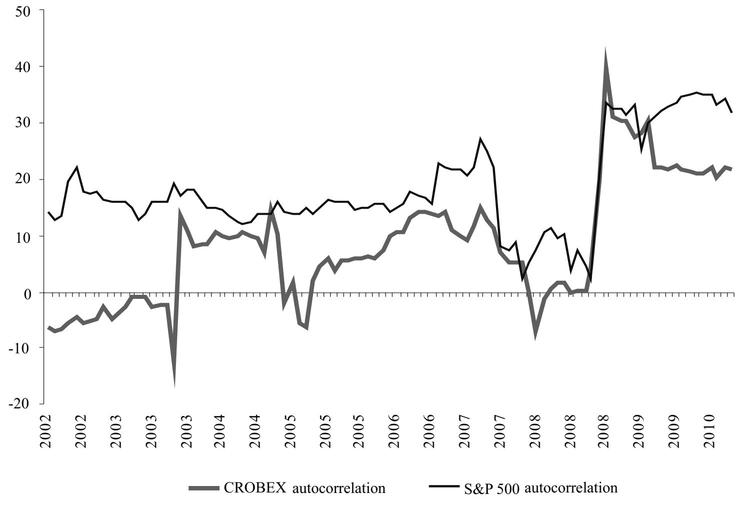
[10] A figure with daily data, not given here, is very similar. It also shows rapid transitions of autocorrelation characteristics of time series of monthly price changes. Notice that the Croatian monthly time series exhibits two additional periods of rapid transitions: one in 2003 (increase) and another in 2005 (decrease). Also note that the presented autocorrelation coefficient of monthly returns is significantly different from zero: on the 60-month sample, significance of the difference from zero at the level of 1% is achieved with a coefficient value of 33.2%; for the 5% significance level, the critical value is 25.3%, while for the 10% significance the critical value is 21.2%.

[11] This is in line with Kunovac's (2011) finding about increase of both intra-market and inter-market correlations in bear periods.

remains ambiguous. However, it is known that shifts in risk preferences (risk aversion) could be one of their main determinants (Pesaran, 2010).

Figure 3

Autocorrelation coefficients of monthly returns on the CROBEX and S&P 500 indexes on the 60-month moving time samples from March 2002 to May 2010 (%)



Sources: Zagreb Stock Exchange (2010), Lo (2004), Shiller (2010) and authors' calculations.

In this particular case, one may assume that events during the crisis of 2008-2009 played a key role in generating similarities between the two markets. Common exogenous shocks spreading over the complex system of globally interconnected capital markets caused similar changes in autocorrelation characteristics of price changes in distant markets. Excluding from observation the crisis period from August 2007 on, the linear correlation coefficient of successive autocorrelation coefficients in Croatia and the U.S. falls to 24% from March 2002 to July 2007, confirming that similarities arose in the crisis period only. A similar result is obtained by calculating a simple correlation of monthly returns. The linear correlation coefficient of monthly returns on the CROBEX and S&P 500 indices is twice as high in the overall period as that in pre-crisis period: it was 62% in the period from February 1997 to May 2010 and, when the crisis period is excluded and the period up to July 2007 included, it stands at 31%.

This finding, however, does not solve the whole puzzle. In the pre-crisis period, the autocorrelation coefficient for monthly data moved close to zero in Croatia. As a rule, it did not exceed 10%. In the light of critical values, this means that the Croatian market was efficient at monthly frequencies. In the same period, the autocorrelation moved around 15% in the U.S., with much smaller variations in successive time periods. Accepting the thesis that the monthly autocorrelation coefficient represents a measure of (in)efficiency, one may conclude that the Croatian market was nearly as efficient as the U.S. market in the decade preceding the crisis.

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Here we urge the reader to recall our introductory discussion on market (in)efficiency. Correlation of successive price changes can be interpreted as a measure of (in)efficiency under the restrictive assumption that an efficient market is represented by a random walk. When this assumption is relaxed (by introducing the martingales and/or rational expectations definition of efficient market), an autocorrelation different from zero may emerge in an informationally efficient market. What happened after collapse of Lehman Brothers in both markets is neither a surprise nor a sign that the market became inefficient. What is surprising is the absence of autocorrelation before the autumn of 2007 on the Zagreb Stock Exchange. It points to the fact that an even underdeveloped market may be efficient.

Intriguing results obtained on monthly data called for a test on daily data (table 1).

For CROBEX, the autocorrelation coefficient of daily price changes exceeds the critical value at the level of 1% in 809 days or 38.5% of the total number of days in the sample. At the 5% level, the critical threshold is exceeded in 962 days or 45.8% of the total number of days in the sample. These are strong indications of inefficiency for the whole period – same result as with monthly price changes.

Table 1

Autocorrelation of daily changes in the CROBEX and S&P 500 indices in the period from 2 January 1997 to 2 June 2010

	CROBEX					
	Pre-crisis period (a)			Overall period		
	Number of days = 1,379	Significance level (b) 5%	Significance level (b) 1%	Number of days = 2,100	Significance level (b) 5%	Significance level (b) 1%
Number of days when critical values are exceeded	-	281	128	-	962	809
Share of days when critical values are exceeded in the total number of days	-	20.1%	9.2%	-	45.8%	38.5%
	S&P 500					
	Pre-crisis period (a)			**Overall period**		
	Number of days = 1,402	Significance level 5%	Significance level 1%	Number of days = 2,207	Significance level 5%	Significance level 1%
Number of days when critical values are exceeded	-	16	8	-	821	813
Share of days when critical values are exceeded in the total number of days	-	1.1%	0.6%	-	23.7%	23.5%

Notes: (a) 1 August 2007 is set as the date when the crisis began and is not included in the calculation; (b) CROBEX critical values are 7.3% for the significance level of 1% and 5.6% for the 5% significance level. Critical values for the S&P 500 are approximately 0.1 percentage point lower (due to the slightly larger sample).

Sources: authors' calculations based on daily ZSE data for the CROBEX and for the S&P 500 Reuters DataLink (Online data vendor), MetaStock v. 10.1.

Excluding the crisis period following 1 August 2007, the coefficient exceeds the critical value at the level of 1% in 128 days or 9.2% of the total number of days, while the number of days when the critical value is exceeded at the 5% significance level increases to 281 days or 20.1% of the sample. The result is different for the pre-crisis compared with the whole period: at a sufficiently high level of statistical stringency; the number of successive time periods with the autocorrelation coefficient different from zero is reduced to below one-tenth. It is difficult to conclude whether this result means that the Croatian capital market was inefficient – particularly in view of the fact that coefficients are very small and, as a rule, do not exceed 15%. Taken together, two pieces of information (marginal statistical significance and size of coefficient not exceeding 15%) were hardly useful for stock traders. Accordingly, we conclude that daily data do not strongly contradict the finding obtained on monthly data that the Zagreb Stock Exchange represented by CROBEX was an efficient capital market prior to recent crisis.

However, the U.S. capital market was very efficient in the pre-crisis period as only 1.1% and 0.6% respectively of coefficients exceeded critical value (in addition, coefficient values did not exceed 2% over the 2003-2007 cycle). The percentage of observations above critical value rises to over 20% when the crisis period is included in the observation. A comparison of these results with those of Lo (2004) leads to the conclusion that it is much more difficult to discover autocorrelation of returns on daily data than on monthly data.

4.2 TRADING TEST: RULE

The notion that a market is to some extent inefficient in statistical terms has no useful application if this supposed inefficiency cannot be used for profit. On the other hand, there is no widely accepted theoretical guidance regarding implications for market efficiency if one finds a profitable trading rule. Notwithstanding theoretical problems, finding profitable trading rules provides intriguing information for both academics and market practitioners.

To date there has been no disclosure of any practicable investment strategy and/or trading system that would yield above-average profits in the Croatian capital market. However, the remainder of this paper will show that it is relatively easy to establish and disclose a trading rule that can beat the market and we hope to provide a plausible explanation why is this possible in section 5.

In the brief literature overview, it was pointed out that more recent research found many trading systems that beat the market using past data. Also, better results were achieved by using longer-term trading systems than short-term trading strategies. The problem of short-term trading systems (apart from significant transaction costs) is that they operate at extremely high levels of noise. The shorter the observation period, the greater is the "noise". This is particularly valid at intra-day and daily intervals (Elder, 2002). Over longer time horizons, noise becomes smaller and the picture becomes clearer.

Long-term trading systems/rules are created with intent to obtain many fewer trading signals (to diminish transaction costs), so as to keep investors in harmony with the dominant trend for as long as possible. Long-term systems want to take the best from the *buy and hold* strategy – participation in the periods of stock price growth and avoidance of the worst – occasional sharp falls in portfolio value.

The results and a graphical presentation of the simulation of 50/200 EMA trading rule on CROBEX are shown in table 2 and figure 4. Results are interesting, to say the least. Using a simple and generally-known trading rule, the hypothetical investor considerably exceeded the return of the Croatian stock market. The initial capital of 100,000 monetary units increased to 291,088 in thirteen years, while the corresponding investment in the CROBEX ended the same period with the portfolio value of only 165,632. Annual returns were 8.56% and 3.95% respectively. The system beat the CROBEX not only with regard to return; not less important is the fact that it was achieved at much less risk. The system was invested in the market for only 1,996 of the total 3,250 days or 61.41% of the overall period. It thereby evaded the major portion of losses during the bear market years (1998-1999 and 2008-2009) with timely entries and long-enough presence during the bull market years (2000-2002 and 2004-2008). The only weakness of the system is the generation of a relatively large number of false signals – five out of the total seven trades ended with a loss. However, the average profit from good signals (135,576) was several times higher than the average loss on false signals (21,977). In thirteen years, the system gave no more than two false signals in a row.

Table 2

Testing the 50/200 EMA system and comparison with the CROBEX index in the period from 2 September 1997 to 2 September 2010

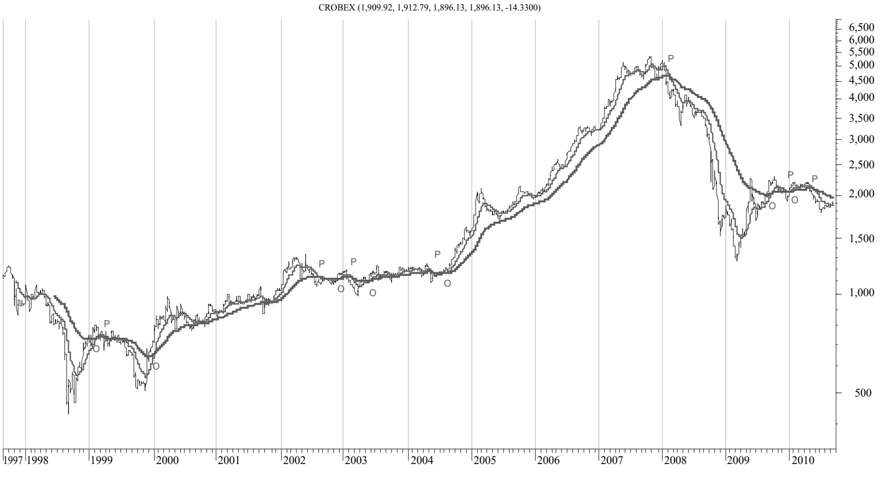
	Closing portfolio value (mu)	**Average annual return (%)**
CROBEX	165,632	3.95
50/200 EMA	291,088	8.56

Total number of trades (*a*)	7
Profitable trades	2
Non-profitable trades	5
Largest number of non-profitable trades in a row	2
Average duration of profitable trades (in days)	766
Average profit per profitable trade (mu)	135,576
Average duration of non-profitable trades (in days)	92
Average loss per non-profitable trade (mu)	-21,977
50/200 EMA profit relative to CROBEX profit	191.15%
Total number of days in the market	1,996

Note: (a) A trade includes one purchase and one sale.

Source: Reuters DataLink (Online data vendor), MetaStock v. 10.1.

FIGURE 4
CROBEX index and 50/200 EMA in the period from 2 September 1997 to 2 September 2010



Source: Reuters DataLink (Online data vendor), MetaStock v. 10.1.

The logical next step is the test of the same trading system on the most developed stock market in the world – the U.S. market. It is somewhat surprising that this simple trading system in the most liquid stock market in the world decisively defeated the *buy and hold* strategy, i.e. the market average (table 3 and figure 5). Results are even more impressive than those for Croatia because there were only five trades of which only two trades were unprofitable and there were no two "false" signals in a row in thirteen years. Once again, there is a huge difference in profit in favor of the system relative to the index (274.60%) made at significantly lower risk – exposure to the stock market risk accounted for only 60% of the total time. This resulted in avoidance of the two sharpest drops in the value in U.S. stock exchanges following the Great Depression – the bear markets of the 2000-2002 and the 2008-2009 period, when the S&P 500 index slumped by 49% and 56% respectively.

This finding is very important for the subject discussed here: market cycles from the 1990s on had the largest amplitudes since the Great Depression (1929-1933). The period from 1995 to 2010 is characterized by unusually long, clear and continuous trends. In bull markets between 1995 and 2000 and from 2003 to 2008, as well as in bear markets from 2000 to 2002 and from 2008 to 2009, stock prices strongly trended. Long-term moving averages are ideal instruments for riding these long-term trends. Moving averages, however, are not nearly as good tools if the market does not move in a clearly defined trend, i.e. when the market moves sideways for a long time.[12] In that case, the moving average system creates nume-

[12] The terms "sideways movement" and "without trend" are often used as synonyms. This, however, should be understood only conditionally. In trendless periods, the market does not "stand still" but goes up and down

Table 3
Testing the 50/200 EMA system and comparison with the S&P 500 index in the period from 2 September 1997 to 2 September 2010

	Closing portfolio value (mu)	Average annual return (%)
S&P 500	119,969	1.41
50/200 EMA	174,804	4.39

Total number of trades (*a*)	5
Profitable trades	3
Non-profitable trades	2
Largest number of non-profitable trades in a row	1
Average duration of profitable trades (in days)	626
Average profit per profitable trade (mu)	25,774
Average duration of non-profitable trades (in days)	43
Average loss per non-profitable trade (mu)	-11,607
50/200 EMA profit relative to S&P 500 profit	274.60%
Total number of days in the market	1,966

Note: (a) A trade includes one purchase and one sale.
Source: Reuters DataLink (Online data vendor), MetaStock v. 10.1.

Figure 5
S&P 500 index and 50/200 EMA in the period from 2 September 1997 to 2 September 2010

Source: Reuters DataLink (Online data vendor), MetaStock v. 10.1.

rous "false" signals, which generate many small losses in a row. Looking at historical stock price charts going back several decades, one sees many periods when the market moved sideways for months, even years (most notably, the 1966-82 period).

When the testing period is expanded to several decades (table 4), the *buy and hold* strategy finally gains advantage over attempts to time entries and exits from the market: the closing value of the market portfolio is 6.4 million monetary units vs. 5.2 million monetary units made using the moving averages crossing. The trading system's profit is almost one-fifth smaller (19.20%) than that of the index.

Table 4

Testing the 50/200 EMA system and comparison with the S&P 500 index in the period from 3 January 1950 to 2 September 2010

	Closing portfolio value (mu)	Average annual return (%)
S&P 500	6,477,380	7.11
50/200 EMA	5,252,740	6.74

Total number of trades (*a*)	29
Profitable trades	18
Non-profitable trades	11
Largest number of non-profitable trades in a row	2
Average duration of profitable trades (in days)	554
Average profit per profitable trade (mu)	282,049
Average duration of non-profitable trades (in days)	85
Average loss per non-profitable trade (mu)	-60,024
50/200 EMA profit relative to S&P 500 profit	-19.20%
Total number of days in the market	10,918 (71.51%)

Note: (a) A trade includes one purchase and one sale.

Source: Reuters DataLink (Online data vendor), MetaStock v. 10.1.

Two conclusions arise: (a) a thorough verification of trading system's validity must be based on longer time series; and (b) in the long run, the EMH (the *buy and hold* strategy) wins – if one disregards the risk. The trading system is indeed less profitable for investors, but that profit is earned with much less risk: an investor is

rather whimsically (a good illustration is the CROBEX movement from 2002 to 2004). In such periods, the *buy and hold* strategy is not likely to show great returns, but neither will it show big losses. On the other hand, the use of moving averages in the same period will cause frequent market entries and exits in futile attempts to catch trends that never form. Although these losses are relatively small, if the market is without a trend for a longer period of time, small individual losses may eventually turn to a large one.

exposed to the stock market risk only 71.51% of the time. What that practically means is that the investor was kept safe of the most vicious bear markets of the second part of the 20th and early 21st century – 1969-70, 1973-74, 2000-02 and 2008-09, as well as numerous minor ones[13]. The price paid for this insurance is the occasional trading "whipsaw" which in time compounds to a somewhat lower profit than the buy and hold strategy.

5 DISCUSSION ON PROBLEMS WITH INTERPRETING THE RESULTS

Strikingly similar changes in autocorrelation of successive changes in stock prices in Zagreb and New York do not represent a surprise. Risk aversion and changes in risk attitudes can produce autocorrelation of price changes. This does not imply that changes in risk preferences can explain every situation of ambiguity involving theoretical priors and empirical results.[14] For example, the speed of learning of sophisticated traders is an issue of critical importance for the interpretation of empirical results but is only weakly reflected in the literature. If sophisticated traders emerge in every market (which equals an assumption that there are always some smart people around) and if only a few of them are strong enough to move the market toward the state of efficiency, statistical similarities between Croatian and U.S. capital markets in the period before the crisis would hardly look surprising. Although it has been more than 30 years since the seminal contribution of Grossman and Stiglitz (1980), we still do not know much about the costs of information acquisition and their impact on market processes, not to mention their relations to the speed of learning.

Our analysis of the 50/200 EMA trading rule provokes an additional question about the nature and speed of learning. Recall that our trading rule, which beat the CROBEX, generated seven trades of which five were losing ones and only two were profitable. Absolute return on profitable trades was much higher than absolute return on losing trades, so the strategy won against the market index. What kind of learning, preferences and investment horizons are required for an investor to stick with a winning trading rule 50/200 EMA in the long run? Two loss making trades occurred in a row, so one can try to put oneself in the shoes of an investor who invests with a mutual fund whose manager sticks with the rule, but after 2 or 3 years has nothing to show but two loss making trades. An optimal reaction in this case may be liquidating the investment. Also, recall the results from table 4: the EMA 50/200 trading system lost against the buy and hold S&P 500 strategy

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[13] The only exception here is the crash of 1987 which happened so fast that the long-term oriented system had not enough time to adapt.

[14] In the last decade, a large body of literature has been developed attempting to model stock price behavior within a system populated by different types of agents (see e.g. Brock, Hommes and Wagener, 2005; and Verbič, 2008). This literature is important as it allows modelling the market as a complex eco-system populated by different types of actors who initially have different risk preferences that change in different ways. The origins of this strand of literature can be traced back to Black's (1986) idea of "noise traders". Interactions of different types of traders (e.g. Black's noise traders and Fama's sophisticated traders) can produce complex dynamics of asset prices. For example Shefrin (2002) showed that sophisticated traders may abstain from trading even when they see a profit opportunity if they assess that risks increased. This may create closed loops reflected in sharp and clear trends as Fama's sophisticated traders stop acting and bubbles are formed.

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from 1950 to 2010, but who is the investor for whom 60 years represents a relevant investment horizon?

Hence, the "discovery" of winning trading systems can be criticized from the perspective of the "benefit of hindsight": there is no guarantee that a trading system that was superior in the past would continue to generate the same result in the future. By the same token, there is no guarantee that a superior trading system could be found (except by chance) in the past. In other words, public disclosure of a superior trading system (as is the case in this paper) is always connected to the following question: would it have been so superior if discovered earlier and could it have been discovered earlier except by chance in the first place? These questions are obviously linked with the learning problem: how do market agents learn in real time? It seems that focus of financial theory on information sets came at the expense of lesser focus on actual learning processes. Perhaps more could be learned about market (in)efficiency by directly observing the actual learning processes of market participants than from observing stock price time series and charts.[15]

Relevant investment horizons, costs of information acquisition and speed of learning are closely related with institutional investors' constraints. EMH and its empirical tests usually forget that the most powerful investors are institutionally organized. Financial intermediaries exist, *inter alia*, for the purpose of intermediating between clients with various preferences regarding risk and time. Sophisticated traders are often leveraged and/or managing other people's money. Both constrain their choices. For example, a fund manager – a strong believer in the 50/200 EMA trading system, may be driven out of the market by clients who withdraw their money from her fund if she makes two loss making trades in the first couple of years of operations. So, even if sophisticated trader is able to learn superior rules, maybe her investors cannot follow. It may take a long time for such a sophisticated trader to earn her own capital and/or credibility to convince other sophisticated investors that she has a winning trading strategy. In the meantime, technicians and financial market specialists may continue to discover superiority of the EMA 50/200 trading rule and interpret this as indication of an inefficient market, while in reality this market may be efficient for given risk and time preferences as well as distribution of investors' knowledge.

Generally, the less market participants are regulated and exposed to financial leverage (the more they manage own capital), the better their position to use occasional opportunities that appear in the market due to institutional limitations if they are knowledgeable enough to spot such opportunities and if their risk aversion

[15] Publication of a winning trading system in this paper will allow us or some other author(s) to test the 50/200 EMA rule on CROBEX data in N years. If the same rule again beats the market in N years (backwards), one may logically conclude that the "hindsight problem" had no bearing on this case. The same applies to an issue of secrecy of a winning trading system. The problem could be analyzed even earlier by the "bootstrap" technique.

does not prevent exploitation of such opportunities.[16] Focus on institutional behavior and organization of sophisticated traders may provide deeper insight into the context of market efficiency than a focus on movements in market prices.

Finally, note that we obtained different results in statistical tests vs. trading rules: statistical tests show market efficiency in the pre-crisis period (in the case of Croatia more convincingly on monthly than on daily data) while the trading rule reveals market in(efficiency) in both Croatia and U.S. throughout the whole period under investigation. However, the autocorrelation test ignores the fact that the equity market is only one among many interconnected financial markets. The trading rule's test explicitly allows for portfolio shifts but of very limited nature (there are two assets: equity and cash). Having this in mind, Ball (1978), following Fama (1976), observed that in a partial analysis it is impossible to know whether one tests the empirical strategy itself or the EMH. At the current stage of development of the theory and empirical tests, then, it is difficult to state much more on market efficiency, given empirical approach which we adopted in our work.

6 CONCLUSION

Both the Zagreb Stock Exchange and NYSE recorded significant deviations of the autocorrelation coefficient from zero at monthly frequencies, with noticeably large variations of the autocorrelation coefficient of price changes across time. The analysis of autocorrelation at daily frequencies shows that both markets are inefficient in statistical terms but the conclusion differs for the pre-crisis period when the U.S. market appears to be efficient, while it is impossible to prove the inefficiency of the Croatian market with a high level of confidence. Moreover, a relatively small value of the autocorrelation coefficient of price changes indicates a level of market inefficiency that was probably negligible from a traders' perspective.

The simple moving average crossover trading rule beats the CROBEX index decisively in the 1997-2010 period, but with more losses than gains. The overall profit of the trading system is generated thanks to profits that are several-fold higher than losses in absolute terms. The result suggests market inefficiency, but it is methodologically questionable whether an *ex post* established trading rule could have been established *ex ante* in real time.

The trading rule based on moving average gains a crucial advantage over the market average in long periods of downward trending prices, which are also periods of statistical inefficiency and increase in risk aversion. If the occurrence of statistical dependence of price changes can be explained by rising risk aversion, the results of the trading rules analysis are compatible with those of the traditional

[16] Regulation and leverage obviously limit the set of possible transactions as they reduce the amount of risk that can be taken per unit of exposure and/or transaction.

statistical analysis. Hence no wonder that the same trading system credibly beats the S&P 500 index in the same observed period (from 1997 to 2010), which is characterized by clear trends. However, the success ratio of the system relative to the market average is not clear over a very long period. Results achieved by the system from 1950-2010 were lower than those obtained from holding the S&P 500 index but they came with significantly lower risk.

In conclusion, statistical and trading rule analyses do not yield conclusive results regarding market efficiency.

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