



Emerging Markets Queries in Finance and Business

Stock market efficiency and the MACD. Evidence from countries around the world

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Abstract

This paper assesses the state of informational efficiency in stock markets of 75 countries around the world by empirically evaluating the economic relevance of a very popular technical analysis indicator, namely the Moving Average Convergence Divergence. There are many published papers that evaluate market efficiency around the world, but none looks at as many countries as this one does. In total, 1336 companies are selected in the sample, with temporal data starting January 1st 2001 and ending December 31, 2012. The methodology used here is based on trading simulation using an optimized trading rule that is applied on out of sample quotes. To be in accordance with the latest guidelines in the field, several statistical tests, including a bootstrap based one, are performed to validate the estimators, thus ensuring bias-free results and more relevant conclusions. Several important statements can be made based on the obtained results, the most important being that traders using the MACD as a technical analysis investment method on the stock market could some times and for certain companies obtain abnormal cost and risk adjusted returns, this pointing out that the world's stock markets present important inefficiencies.

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1. Introduction

This paper focuses on evaluating stock market efficiency in countries around the world by empirically evaluating the performances of a very popular technical analysis indicator, namely the Moving Average

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Convergence Divergence indicator developed by Gerald Appel (1979). Technical Analysis is made up out of a wide variety of practical investment methods that use past trading data to try and forecast future price behavior and thus try to make abnormal trading profits. This, however, comes into conflict with the postulate of the current financial market paradigm, the Efficient Market Hypothesis, which states that even in the case of a week from efficient market, as described by Fama (1970), past information is incorporated into the current price evolution, thus it cannot be used to generate higher than normal returns for the category of risk the investor exposes himself to. Fama and Blume (1970) stated that the ultimate criterion in determining market efficiency is always practical, so the true market nature, in the sense of information efficiency, cannot be determined until all practical methods have been tested and validated or invalidated on the market. This is what this paper tries to do, although by using a single technical indicator. By evaluating the profitability of the MACD, we indirectly evaluate its level of information incorporation into trading prices. If stock markets are weak form efficient, then the past profitability information of the MACD should be incorporated into current trading prices, thus a technical analyst would find it impossible to use this indicator in order to make abnormal profits. Even more so, the profitability should constantly decline over time.

There is a tremendous volume of published papers that focus on evaluating market efficiency on stock markets throughout the world. They started at the down of the 20th century and continue to be published in exponential numbers by academic journals around the world, especially when 2013 saw the Nobel Prize in Economics go to three exponential figures in this field. There is no point here in reviewing the lot. A handful of literature reviews are now available, among which the very interesting historical evolution depicted by Dimson and Mussavian (1998) is recommended by the author. The employed methodologies are very diverse, ranging from simple autocorrelation tests to very complex optimization algorithms, like Neural Networks, Genetic Evolution or Particle Swarm Optimization. Let us focus on what this paper is about.

This study uses basic trading simulation to determine the profitability of the tested technical trading rules. The methodology tries to mimic what actual investors do in practice when trying to apply mechanical technical analysis trading rules. Thus, we start with the question “What trading method should I use in order to obtain a sustainable trading profit?” The answer to this question leads to seeking the most successful past trading rule. Assuming that the investor specializes in one technical analysis indicator, like, let’s say, the MACD, then the question translates into “What parameter combination should I use?” This leads to optimization being employed in order to determine the parameter combination that maximizes a predetermined return measurement on past trading data. When the optimum rule is discovered, it is then applied in actual trading. Here, actual trading is substituted with trading simulation on out-of-sample data. This method is not new, with many authors employing it in their studies, as Park and Irwin (2007) show after dubbing it “the Standard Method”. The main problem of the approach is that it can easily generate false discoveries due to the data snooping bias inherent in optimization techniques. To counter these effects, several tests are employed in order to evaluate the statistical relevance of the calculated estimators. In this paper, two kinds of tests are used: basic t-tests and a more complex bootstrap based one. These statistical tests are also not new, as bootstrap based verification was used in the 1990’s, with Brock, Lakonishock and LeBaron (1992) being among the most successful in promoting this method.

By this time the reader may wonder what contribution to existing literature does this paper have? The answer is that there are three ways in which this paper contributes:

- First, the trading simulation is improved by incorporating all measurable trading costs that an investor encounters when he/she is active in the market.
- Secondly, a different return indicator is used as the target optimization measurement. The advantages it brings over already implemented indicators are numerous and are detailed later.
- Thirdly, the amount of data used and also its quality are a big plus versus the majority of existing papers. Here, 1268 companies from 75 different countries are studied.

All of the above mentioned contributions aim to generate more reliable conclusions when talking about

stock market efficiency at a global level.

In order to achieve the goals, the remainder of the text is structured as follows: chapter 2 details the MACD indicator and the way researchers have used it so far in empirical testing. Chapter 3 presents with greater detail the methodology employed. Chapter 4 presents the results and comments on them while the final chapter is reserved for conclusions and remarks.

2. The Moving Average Convergence Divergence indicator

Technical Analysis indicators are basically linear functions that use past trading data, like open, high, low or close prices, volume, open interest, advances, declines and so on, to calculate recurrent values, which are later analysed by the technical analyst to make investment decisions. The Moving Average Convergence Divergence (MACD) was introduced by Gerald Appel (1979) and is one of the most popular technical indicators. The basic formula of the MACD is:

$$MACD(n_1, n_2) = MA(C_t, n_1) - MA(C_t, n_2) \quad (1)$$

where $MA(S, n)$ is a Moving Average calculated for the series S over an n -length window, n_1 is the window length for the first moving average and n_2 is the window length for the second moving average. As it can be plainly be seen, the MACD is a simple subtraction of two moving averages, with the first one being intended of being a short-term average and the second one a long-term average, so $n_1 < n_2$ is the basic integrity condition. Starting from this, the interpretation is simple: the higher the MACD, the more the price has risen over the last n_1 observations when compared with the last n_2 observation and so the stronger the upward trend has been. Likewise, a small negative MACD indicates that the price has fallen over the last n_1 observations when compared with the last n_2 observations and so the stronger the downward trend has been.

MACD is an oscillator, because it's mean-reverting around zero. It is also an indicator that measures price momentum, meaning the strength and direction of a trend in a stock's price. As all momentum indicators, the way an investor uses MACD to trade is diverse. The simplest way is to track the indicator values and look for signs of market trend change. The trend can be considered changed when the indicator passes through its mean-reverting point, thus pointing out a new past market trend, which in turn points to a new future market trend. If a trend following strategy is implemented, this generates a trading signal in favour of the forecasted trend. The MACD used in this way acts just like a moving average crossover rule. This strategy has the disadvantage that it's lagging the price, meaning that the trend reversals are detected after they actually happen. Another way of using momentum indicators is by trying to detect overbought and oversold situations. This is where its oscillator characteristics come into play. When the market is overbought (past market trend has been excessively bullish) or oversold (past market trend has been excessively bearish) then an investor using a contrarian strategy would trade against the current market trend, anticipating a reversal or at least a temporary retracement. The problem with the MACD in detecting overbought and oversold situation is that it is dependent upon the price level. The higher the asset price in terms of the trading currency, the higher the values recorded by the MACD, so a general overreaction level similar to the Relative Strength Index (another popular momentum indicator) does not exist. In order to correct for this deficiency and use the MACD for overreaction trading in different, a percentage MACD may be used, its formula being:

$$MACDp(n_1, n_2) = MA(C_t, n_1) / MA(C_t, n_2) - 1 \quad (2)$$

So using $MACDp$, overbought or oversold situations are detected when extreme values (when compared with past values) are reached.

Another way of using momentum indicators is with a signal line, which is an exponential moving average of

the actual indicator. This is the primary way of using MACD that its proposer intended for it. In this scenario, a trader must calculate the MACD and an n3-day moving average of it called a signal. When the MACD crosses over the signal line, then an indication that price momentum is changing is provided, thus the trader buys or sells depending on the way the MACD and signal line crossed. The formula for the signal line is:

$$S=EMA(MACD(n_1,n_2),n_3) \quad (3)$$

This trading method was developed in order to counter the lagging deficiency of most momentum indicators. The crossing of the indicator with the signal line is an early warning that something may happen in the market. In technical analysis terms, this strategy is most of the times referred as MACD(n1,n2,n3).

The last possible way of trading with a momentum indicator is by looking at convergence/divergence signs versus the market price. If the market price reaches a new local high/low but the MACD does not, then a divergence is indicated, this signalling the possible end of the current market trend and a beginning of a new one.

The Moving Average Convergence Divergence indicator has been used before in international literature for studying market efficiency, although not as often as it should be implied by its popularity among investors. For example Bodas-Sagi et al (2009) used genetic evolution parameter optimization and compared the performances of the MACD with the buy-and-hold strategy for the Dow Jones Industrial Average Index. They found that it performs much better than the benchmark, although the results were not adjusted for trading cost and risk. Armour et al (2010) tested two technical analysis rules, including the standard MACD(12,26,9) one, on 20 years of data of the Irish Stock Market Main Index and found that the MACD rule underperformed the buy and hold benchmark. However, given that the second rule (a simple moving average one) outperformed the benchmark, they concluded that the moving average method could shed some doubt about the efficiency of the Irish stock market. Chen et al (2011) examined six trading rules, including a MACD-based one, on daily data of the Danish stock market index and found that all the buy-sell differences under trading rules of either two-indicator or three-indicator combinations were positive with significant t-stats to reject the Efficient Market Hypothesis, thus concluding that technical analysis had solid predictive power in the stock market and could discern recurring-price patterns in the case of the Danish stock index. Kara et al (2011) incorporated the MACD and four other technical analysis indicators into artificial neural networks and support vector machines in order to predict the direction of the Istanbul Stock Exchange (ISE) National 100 Index and found that both the ANN and SVM models showed significant performance in predicting the direction of stock price movement, thus implying that both the ANN and SVM are useful prediction tools for this topic. Abbey and Doukas (2012) examined four technical analysis indicators, including the standard momentum MACD(12,26) rule, in currency trading by individual currency traders and found that technical analysis is negatively associated with performance, thus concluding that currency traders that used this kind of technical analysis rules suffer from reduced performance. Chen and Metghalchi (2012) then tested 32 models based on different combinations of six indicators, including the MACD, on the stock market index of Brazil for the 1996-2011 period and found that applying a variety of trading rules with single, double and triple indicators did not support the predictive power of technical analysis, thus concluding that the Brazilian stock index was weak-form efficient. Metghalchi et al (2012) examined the predictive power of 66 technical analysis trading system in which they incorporated some MACD rules for the Taiwanese stock market from 1990 to 2010. They found that the majority of the rules had predictive power in this market, although they did not proved that the rules can be used to generate economic profit. Biondo et. al. (2013) compared the performances of a random strategy versus several technical analysis ones, including the RSI, for daily stock exchange indexes of the United Kingdom, Italy, Germany and the United States for the 1989-2012 period and found that standard trading strategies and their algorithms, based on past history of the time series had occasionally the chance to be successful inside small temporal windows, although on a large temporal scale performed on average not better

than the purely random strategy, which, on the other hand, was also much less volatile, thus concluding that for the individual trader, a purely random strategy represents a costless alternative to expensive professional financial consulting, being at the same time also much less risky and indirectly supporting the EMH for these markets. Du Plessis (2013) examined the effectiveness of the MACD technical analysis strategy versus the buy-and-hold one for the South African Stock Market and found that the benchmark investment strategy is more effective than the MACD one in this market.

There many more papers in which MACD's performances are evaluated and conclusions regarding market efficiency are drawn from it, but none is more complex than this regarding the diversity of studied markets and the volume of studied data series.

3. Methodology

3.1. Overview

This study tests the performance of two independent trading strategies, the first being based on the MACD trend following rule and the second on the MACD vs. Signal rule. Evaluating the two strategies is important as the goal of this paper is to assess the overall characteristics of the MACD, in order to evaluate how well the markets incorporate the information provided by it. The conducted tests try to answer the following questions:

- Is the MACD capable of generating excess economic returns for an investor that uses it on world markets?
- Does the MACD provide surplus information for an investor on the world markets?
- How would one evaluate the informational efficiency of world stock markets based on the above findings?

There are several testing approaches implemented in the international literature for these kind of papers, these being very well documented by Park and Irwin (2007): (a) **the standard method** that uses in sample optimization followed by out of sample confirmation, (b) **the bootstrap confirmation method**, which is based on the methodology introduced by Brock, Lakonishock and LeBaron (1992), **genetic programming** where researchers attempt to eliminate the data snooping bias by implementing genetic algorithms introduced by Koza (1992), (c) **the reality check** based on the Bootstrap Reality Check methodology introduced by White (2000) and improved by Romano and Wolf (2005), Hansen (2005) and Hsu, Hsu and Kuan (2010) and (d) **other non-linear methods**, such as feed forward neural networks or k-Nearest Neighbours regressions. Another important approach not documented there is (e) **the False Discoveries Rate (FDR) test** introduced by Benjamini and Hochberg (1995) and improved by Bajgrowicz and Scaillet (2012).

3.2. Improvements versus standard literature

This paper uses a combination of the Standard and Bootstrap Confirmation methods and then improves on them in accordance with the specifications derived from Timmerman and Granger (2004). Standard procedures imply that trading simulation is performed to evaluate a trading rule's cost and risk adjusted profitability. This means that a rule universe is constructed using the MACD's three possible strategies, then the data samples are divided into several sub-samples. In order to simulate what investors actually do in practice, trading is conducted using only the best rule that has been selected from the whole universe following optimization in the previous time window. In other words, the best system from the trading universe in a sub-sample (called a "training window") is chosen using optimisation of a target return measurement and then the results of actual trading are calculated on the following sub-sample ("trading window"). This is done in order to simulate the backtesting routine that investors actually use. By calculating the results in a new sample, these should reflect what investors could actually gain using the MACD trading strategies.

But, as stated earlier, the methodology used here is improved versus standard literature, as the following are implemented:

The geometric M2 for Sortino excess return (denoted ExM2) is used as the target return measurement in optimisation. This indicator uses the Modigliani-Modigliani (1997) approach to risk adjusting but substitutes the overall risk with depreciation risk. This differs from the usually used simple return or Sharpe ratio and is implemented here because it combines several very useful characteristics. (a) it computes an excess return, in the sense that it compares the result obtained by the trading strategy used by the investor with a benchmark strategy and reports the excess performance. (b) The results are adjusted to risk, but not total risk, as it is usually done in the literature, but downside risk (the specific risk of portfolio depreciation), this being the really important risk for an investor. In other words, the results are adjusted with the risk differential of the investment portfolio compared to the benchmark portfolio. (c) It is an indicator whose values are easy to interpret by any investor, since it quantifies the geometric difference between the portfolio return and the return of the benchmark strategy.

The trading simulation procedure to calculate return and risk for a trading strategy on a given data sample is improved in order to account for the extra trading costs generated by liquidity risk. This is done by simulating trading at the least favourable prices for the investor, these being the high price when buying and the low price when selling. Traditionally, researchers use only the daily close price as the trading price. The problem is that any trade bears an extra cost in the form of the bid-ask spread, this mainly being influenced by the risk of trading in that market (a combination of liquidity risk, transparency risk and so on). Many empirical studies, including Timmermann and Granger (2004, p. 16), showed the importance of taking into consideration both observable costs (commissions, fees, etc.) and unobservable costs (bid-ask spread). This study adjusts the returns with known observable costs, but also with part of the non-observable costs by trading at the least favourable market prices. Here, the low-close (for short trades) or high-close (for long trades) daily spreads are used as a proxy for the unobservable cost generated by the higher liquidity risk. These basically behave similar to the bid-ask spread: when liquidity is lower, the risk is higher and the spreads are higher. Thus, by buying at the highest price and selling at the lowest price, an extra cost is included in the analysis. Ideally, the actual daily average bid-ask spreads should be used, but this kind of data is not freely available, while the implemented approach should be reliable enough in generating non-biased return estimators.

As optimization implies that overfitting (data mining) exists, two non-standard bootstrap based tests are employed in order to statistically evaluate the returns in the trading window. These are completed by a standard t-test of aggregated estimators. Both ensure that the results are not subjected to data snooping biases.

Shorter data windows are used. Here, up to 12 sub-samples have been created by dividing the initial data sample, which spans 12 years, into separate years. The main reason for doing this is that it mimics even closer what investors actually do in practice. Menkhoff (2010) proved that investors that use technical analysis methods have a relative small investment horizon, of up to 6 months. They tend not to keep using the same trading strategy for large periods of time and try to adjust to the latest market conditions.

Another improvement is the implementation of only long trades, because of the known market restraints for short selling in many countries, this ensuring that results for different markets are comparable.

One final improvement is the exclusion from the analysis of optimized rules that generated less than two in-sample transactions, because one-trade rules are effectively similar to the buy-and-hold rule. This ensures keeping only the true active trading rules in the rule universe and eliminating the cases in which in sample rules were selected based on perfectly over fitted passive trades. Only active trading rules are filtered because in this paper a strategy based on a technical analysis indicator is tested, this being fundamentally an active strategy, and then its results are compared with the passive buy-and-hold strategy to determine if excess returns are generated. There is no point in comparing two fundamentally identical (passive) strategies.

These changes are in accordance with the standards of empirical testing expressed by Timmermann and Granger (2004) because it makes the testing procedure and finally the conclusions more relevant. This same procedure has also been used by Anghel (2013a) when analysing the performances of the Rate of Change indicator on the Romanian Stock Market and by Anghel (2013b) when analysing the performances of the

Relative Strength Index on eight Central and Eastern European countries.

3.3. Trading simulation and return calculation procedure

In order to have accurate results, a testing procedure is implemented to mimic the investment procedure of an actual trader. In this respect, fictive investment portfolios are created with an initial arbitrary value large enough in order for trades to be possible. The market position that must be maintained by the trader is tracked using a signal function (S_t). The signal function shows the position that should be adopted in the market at any one time, with 1 indicating a long position, -1 a short position and 0 indicating that no position should be opened. As three independent MACD-based rules are tested, there is a separate signal function for each of them. For the trend following system, the signal function is:

$$S_t = \begin{cases} 1, & \text{if } MACD_t(n_1, n_2) > c \\ 0, & \text{otherwise} \end{cases}, t \in (1, T) \quad (4)$$

And for the MACD vs. Signal system, the function is:

$$S_t = \begin{cases} 1, & \text{if } MACD_t(n_1, n_2) > S_t(MACD_t(n_1, n_2), n_3) \\ 0, & \text{otherwise} \end{cases}, t \in (1, T) \quad (6)$$

where n_1 , n_2 are the time periods the MACD is calculated on that vary from 0,1% to 99% of the sample length with an increment of 5 days; n_3 is the time window the Signal function is calculated on, this varying from 3 to 45 with an increment of 3 days; c is a constant fixed to zero; $MACD_t(n_1, n_2)$ stands for „the value of the n_1 -period Moving Average minus (or divided by for MACDp) the n_2 -period Moving Average calculated on day t “. Note that n_1 , n_2 , c , c_1 and c_2 are the target parameters in the optimization procedure. This means that they are selected by maximizing the target return measurement ($ExM2^S$). A mistake would have been to fix the parameters as most practitioners do, because this would have severely restrained the rule universe, which in turn would have led to biased results for the MACD rule. The optimization of c_2 is an improvement over what Anghel (2013b) did when testing the RSI contrarian rule. Also note that

Trades are then generated when the signal function changes. Starting with the signal function and its suggested trades, the portfolio function (V_t) can be calculated. This is influenced by the market price changes and the market position indicated by the signal function. The trades first of all change the market position, but they also directly impact the portfolio value through trading costs. As previously stated, in order to have a relevant testing procedure and to avoid a bias in the return estimators, all possible trading costs are taken into consideration. For the direct observable costs, 1% of trade value for Romania and 0.5% for the other countries are used. For the unobservable liquidity-based cost, the low-high spread of the trading day is used. The synthesized formula for computing the portfolio value is:

$$\text{with } C_t = V_t(c + lhs_t) \quad (8)$$

where P_t is the close price on day t , C_t is the cost generated on trading day t , with c being the commission percentage used and lhs_t the percentage low-high spread which is either the low-close or the high-low percentage spread. From the above formula it can clearly be seen that trading is not conducted on the day the signal changes, but on the following one.

For the computation of effective investment returns, the portfolio value function is used as a base. The weekly portfolio log returns are calculated to construct a return series. Weekly returns are computed because they are less noisy than daily returns, but are more frequent than monthly returns. For comparison, the returns of the benchmark portfolio are also measured. They are obtained using the same testing procedure, the

difference being made by the signal function, which in the case of the benchmark strategy has the following form:

$$SB_t = \begin{cases} 0, & \text{if } t = 0 \\ 1, & \text{otherwise} \end{cases} \quad (9)$$

Having calculated the two return functions, the final aggregated return indicators can be computed, along with the total risk and downside risk, which are then used in the calculation of the ExM2^S estimator. The following steps are implemented to calculate ExM2^S:

First calculate the Sortino ratio:

$$SR = \frac{r_p - r_b}{\sigma^d} \quad (10)$$

where r_p = investment portfolio total return; r_b = benchmark portfolio total return; σ^d = downside risk of portfolio return (based on weekly returns);

Then calculate the Sortino M2 return:

$$M2^S = r_p + SR(\sigma_b^d - \sigma^d) \quad (11)$$

Where σ_b^d = downside risk of benchmark portfolio (based on weekly returns);

From (1) and (2), the following derived formula can be used for M2^S:

$$M2^S = r_b + (r_p - r_b) \frac{\sigma_b^d}{\sigma^d} \quad (12)$$

Finally, calculate the Geometric M2 for Sortino excess return:

$$ExM2^S = \frac{1 + M2^S}{1 + r_b} - 1 \quad (13)$$

3.4. Optimization and out of sample trading procedure

Optimization refers to finding the combination of parameters that maximizes the target function, this being the ExM2^S. In order to choose the best system from the testing period using parameter optimization, all possible parameter combinations for the two RSI trading systems are first generated. These, in turn, are applied to the data series as per the testing procedure described previously, resulting a series of ExM2^S estimators. The k -th system is chosen as being the best system in the training window:

$$k = \text{IndexOf} \left(\max_{1 < m < M} ExM2_m^S \right) \quad (14)$$

Then the optimal parameter pairs (n_k, c_k) or (n_k, c_{1k}) are found and this are applied on the next data sample. In order to evaluate the economic relevance of the selected systems, each best performing rule derived in the training window is applied to an out of sample series (the next time window), thus obtaining via the same testing procedure an ExM2^S_{os} estimator.

3.5. Evaluation of statistical significance

For a trading system based on technical analysis indicators to be economically relevant the condition $ExM2_{os}^S > 0$ must be fulfilled, that is, the excess cost and risk adjusted return outside the initial testing sample must be positive.

Although this confirmation approach is the preferred one in practice, for a properly scientific confirmation it is not enough. Thus, several tests for the statistical evaluation of the $ExM2_{os}^S$ estimators are performed. To implement these tests, the distribution of $ExM2_{os}^S$ must be known. Since a theoretical approach for its determination is very difficult, if not impossible, and an approach based on a Monte Carlo simulation has the inconvenience of the restrictions imposed on the initial price return distribution, a methodology based on the bootstrap simulation is implemented, which has the advantage that it uses the observed distribution of price returns.

Thus, for the determination of the $ExM2_{os}^S$ empirical distribution using the bootstrap simulation, the following steps are followed:

The empirical distribution of the original market price returns is determined.

10,000 simulations for the determination of the $ExM2_{os}^S$ empirical distribution (denoted R) are performed. Each simulation passes through the following stages:

- A simulated return series is generated using random sampling with replacement from the empirical price return distribution obtained in the first stage;
- A simulated price series based on the simulated return series and the first actual market price is generated for the high, low and close prices;
- The $ExM2S$ indicator for the simulated price series is computed using the testing procedure described previously.

After obtaining the empirical distribution of the $ExM2^S$ indicator, it can be established if the $ExM2_{os}^S$ estimator computed for the best in sample trading system is statistically significant. For this, its p-value is computed:

$$p - value = \begin{cases} 2 * P(r > ExM2_{os}^S), & \text{for } P(r > ExM2_{os}^S) \leq 0.5 \\ 2 * (1 - P(r > ExM2_{os}^S)), & \text{for } P(r > ExM2_{os}^S) > 0.5 \end{cases} \quad (8)$$

This is applicable for a test with the null hypothesis H_0 : the $ExM2_{os}^S$ estimator is statistically different from zero. The null hypothesis is rejected with 95% confidence if $p\text{-value} \leq 0.05$. In this case the estimator is not statistically significant. For the reported results, the statistically confirmed cost and risk adjusted excess return obtained in the out-of-sample window was dubbed the first criteria of economic relevance. A positive and significant return means that the system proved economically relevant for the tested sample.

At the same time, a statistical test can be built for the determination of the general economic relevance of the chosen system for a specific asset, i.e. if it can generate positive cost and risk adjusted returns on a more general level for a tested company, provided that the market conditions remain constant. In order to determine the dismissal or not of the null hypothesis, the probability denoted P1 that the system true excess return is positive is calculated: $P1 = P(r > 0)$, where $r \in R$. The test has the null hypothesis:

H_0 : $P1 > 0.5$ (the system is economically relevant)

H_1 : $P1 \leq 0.5$

The interpretation of the results is straightforward, because the bigger P1 is, the more economically relevant the system is, since it can obtain positive results with a higher probability than a pure random trading strategy that has a 50% chance of success. Thus, H_0 will be rejected if $P1 \leq 0.5$. Remember that P1 is calculated for a distribution derived from 10000 bootstrap simulations, this giving it significant statistical power. For the reported results, this was dubbed the second criteria of economic relevance.

Finally, we want to evaluate the performance of the MACD rules on a more general level, because the above tests apply only for specific companies in a specific time window. To do this, a test for determining if the P1 value is consistently higher than 0.5 for a certain grouping is constructed. Assuming normality of the P1 probability population, the following statistic follows a standard t-distribution:

$$t - stat = \frac{\overline{P1} - 0.5}{\frac{\sigma_{P1}}{\sqrt{n}}} \quad (9)$$

The t-stats and corresponding p-values are calculated when aggregating results by country, by calendar year and, of course, on the absolute general level.

3.6. Data sample

The data sample is comprised out of daily trading price series for the most liquid companies listed on 75 world stock markets starting with January 1, 2001 and up to December 31, 2012. A maximum of 25 companies are retrieved for each country using the market value criteria (stocks with the higher market capitalization are selected first). Note that the actual number of companies in the sample for many countries is smaller because either there are not so many listings on the market, or their liquidity is not sufficient to be considered here. The majority of companies are part of the main national stock market indices. All the data is collected from the Thomson Reuters Eikon for Student platform, available at The Bucharest University of Economic Studies through the PROFIN project and is fully adjusted for capital changes and dividends.

Sample years that have less than 65 trading days are not considered in optimization and testing because of the common knowledge that technical analysis is not applicable for illiquid assets. Overall, there are 1268 selected companies with data lengths varying from 2 years to 12 years (depending on how long they have been listed on the market), this generating a total number of 11684 yearly time windows (sub-samples), from which a number of 10416 are trading windows. For each trading window an equivalent training window (previous time window) exists.

3.7. Methodological limitations

Although the employed methodology possesses several improvements versus the existing literature, it is still not flawless. There are several issues that may be pointed out. Firstly, the simulation is based solely on one technical analysis indicator, namely the MACD. Nowadays, market participants have a very wide range of indicators to choose from. Also, if not considering technical analysis, they have a wide variety of other linear and nonlinear models to choose from. Ideally, several indicators and/or several other models should be combined in order to generate a more complete trading system from an informational point of view. This is not done here mainly because of hardware and software constraints.

Secondly, the considered technical analysis indicator is very old, having been used in practice since the 1970's. Being also a very widely used indicator, it is probable that the information provided by it is already incorporated into trading prices. However, on the plus side, this is not yet proved for and this paper tries to do exactly that.

Thirdly, there is the question if actual investors really use optimization in order to find a trading strategy, or they just stick to standard parameters and improve on them using other indicators or trading techniques that were not considered here (like filters, stop losses and so on)? And in the case that optimization is performed, does it imply scrolling through all possible parameter combinations or just a few? The problem is that this technique tests many trading rules that fundamentally are similar, this being time and resource consuming for a

computer and acting in disfavour of the investor. Clear evidence in this sense does not exist, but one thing is sure: many researchers do implement parameter optimization in this way.

Another question is if the high-low spread used here as a proxy for liquidity cost is adequate? Intuitively, this spread should be higher than the actual market bid-ask spread, thus a larger than normal cost is incorporated into the analysis, this in turn introducing a downward bias for the return estimators. However, in the author's opinion this is not necessarily a bad thing, as it is a more prudent approach that leads to a lower change of dismissing the EMH for the studied markets. On the other hand, it undermines the MACD's economic relevance, if it would exist. But in the absence of actual bid-ask spread values, this should be the best approach.

Finally, there is the problem that not all trading costs have been considered, chiefly among which is the market impact cost of trading. The conducted simulations have no impact on historical trading data, but if investors would have used this techniques, they would have influenced the prices through the excess demand/offer expressed in the market. This, in turn, would have generated extra trading costs for them. The higher the orders, the higher the costs. These are not considered here, although it can be argued that for retail investors that poses low amounts of capital this would make no difference, so the conclusions are fully applicable to them.

4. Results

The appendices show the results obtained in testing. Appendix 1 shows the individual company statistics for the MACD momentum rule, appendix 2 shows the individual company statistics for the MACD vs. signal rule, appendix 3 shows the aggregate cross-sectional statistics for the MACD momentum rule, appendix 4 shows the aggregate cross-sectional statistics for the MACD vs. signal rule, appendix 5 shows the aggregate yearly statistics for the MACD momentum rule and appendix 6 shows the aggregate yearly statistics for the MACD vs. signal rule. Without going into too much details, the following can be observed when analysing the results.

At an individual company level, the results vary greatly for both MACD implemented rules. The cost and risk adjusted excess returns using the MACD momentum rule vary from -106.12% to 857,800.53%, with a mean of -947.61% (not significantly different from zero with a p-value of 0.9910 of the standard T-test. For the MACD vs. signal rule the excess returns vary from -144.23% to 46,987,880.50%, with a mean of -45,122.60% (also not significantly different from zero with a p-value of 0.9991 of the standard T-test). The overall rates of success (the percentage of total cases when the rules are capable of generating excess economic returns) are 26.05% measured with criterion 1 and 33.44% measured with criterion 2 in the case of the MACD momentum rule and 26.83% measured with criterion 1 and 38.34% measured with criterion 2 in the case of the MACD vs. signal rule. These results first of all mean that the two examined rules have similar success rates when applied on a global scale. More importantly, the fact that the success rates are significantly below the 50% threshold means that overall the MACD indicator is not capable of generating systematic excess returns, although this does not tell us much about the economic relevance of the MACD because a global excess return can be achieved even with low positive trade rates. Instead, this finding confirms the belief among technical analysts that trend-following strategies, like the two MACD rules examined here, have low success rates. The T-tests conducted at the general level for the average P1 probability, which is 38.13% in the case of the MACD momentum rule and 41.56% for the MACD vs. signal rule, support the above findings, these having t-stats and p-values that reject the null hypothesis of economically relevance. In a preliminary conclusion, the EMH cannot be rejected at a general level for world stock markets when using the MACD indicator as a testing/trading method.

Things get more interesting when aggregating results by country. The data presented in appendices 3 and 4 show the same heterogeneity between different countries that was present at company levels, but here, having more tests per country, a clear statistical inference can be made. The results show that there are six countries

for which the rate of success for one of the two criteria for the MACD momentum rule surpasses 50%, namely Bahrain, Cyprus, Kazakhstan, Morocco, Namibia and Ukraine. Also, there are eleven countries for which the rate of success for one of the two criteria for the MACD vs. signal rule surpasses 50%, namely Bulgaria, Bosnia & Herzegovina, Cyprus, Jordan, Kazakhstan, Lebanon, Latvia, Morocco, Namibia, Serbia and Ukraine. However, this does not mean much in terms of market efficiency, but just that in this countries the MACD rules are more successful than in the rest. On the other hand, and more importantly, there are much more countries for which the average cost and risk adjusted returns are positive and statistically significant using both rules. Because the list is fairly long, only the abbreviations will be used to enumerate them. They are: AE, AR, BG, CL, DE, EG, FR, HU, JO, JP, LK, MA, OM, PE, PH, PK, PL, SA, SE, SG, TH, TR, UK and US for the basic MACD momentum rule and AE, BH, DK, EE, EG, HU, IL, KW, LV, NO, OM, PT, SA, SK and VN for the MACD vs. signal rule. This means that, in total, there are 34 countries for which it is possible to obtain abnormal profits using one of the two MACD trading rules.

When the average P1 probability is analysed, the rules are not as successful: only for CY and UA does the MACD momentum rule manages to obtain above 50% economical relevance probability, while for the MACD vs. signal rule there are four countries, namely CY, KZ, NA and UA. Nevertheless, each of these two examination criteria show us that there are countries in the world for which technical analysis can be employed with great success, this in turn leading to the conclusions that there are stock markets for which the efficient market hypothesis can be rejected. The reported results also suggest that market efficiency is a relative concept, not remaining constant trough space and, as we will see later, trough time. To prove this, Table 1 shows a ranking that can be constructed in order to evaluate relative informational efficiency based on the computed P1 average probability, with the top ranked countries being more efficient than the lower ranked countries.

Table 1. Relative efficiency by country

Country	Ranking using MACD momentum rule	Ranking using MACD vs. signal rule	Overall Ranking
CO	13	2	1
AU	4	13	2
AT	3	15	3
CL	11	11	4
BE	5	26	5
CA	9	22	6
IN	29	4	7
ID	27	7	8
FR	22	21	9
HK	24	19	10
BR	8	36	11
DK	17	28	12
MX	44	1	13
AR	2	45	14
NG	47	3	15

MY	45	8	16
CN	12	43	17
AE	1	55	18
ES	20	37	19
PE	52	6	20
LK	39	20	21
MU	43	16	22
CH	10	50	23
FI	21	42	24
DE	16	48	25
PK	54	10	26
KE	34	31	27
PH	53	14	28
EG	19	49	29
KR	35	33	30
TH	66	5	31
CZ	15	59	32
NZ	50	24	33
IS	30	46	34
BG	6	72	35
BH	7	71	36
EE	18	61	37
IL	28	53	38
OM	51	30	39
PL	55	29	40
ZA	75	9	41
HR	25	60	42
IT	31	54	43
TR	68	17	44
VE	73	12	45
SG	63	23	46
LT	40	47	47
SE	62	25	48
NL	48	40	49
CY	14	75	50
GR	23	66	51
HU	26	63	52
UK	71	18	53
QA	57	34	54
SA	61	32	55

JP	33	62	56
RO	58	39	57
LV	41	57	58
US	72	27	59
JO	32	69	60
TN	67	35	61
KW	36	68	62
RU	60	44	63
NO	49	58	64
LB	38	70	65
PT	56	52	66
MA	42	67	67
TW	69	41	68
KZ	37	74	69
SI	64	51	70
NA	46	73	71
SK	65	56	72
RS	59	65	73
VN	74	64	74
UA	70	76	75

This tells us that the most efficient country in the sample is Colombia, followed by Australia and Austria, while the least efficient are Serbia, Vietnam and Ukraine. Surprisingly, the biggest market in the world, the United States, is only in the 59th position, this possibly meaning that market efficiency is not correlated with market size or liquidity.

Even more interesting are the results aggregated by year. Yearly fluctuations of the success rates and of the P1 probability can be seen, but in most of the cases, these vary below the 50% threshold for both rules. However, four notable cases can be seen for which this is not true and both success rates and average P1 probability clearly surpasses the threshold, these being for the years 2008 and 2011 for both rules. The success rates in 2008 are 75.80% using the first criterion and 92.29% using the second criterion for the MACD momentum rule and 68.49% and 94.63% using the MACD vs. signal rule, while for 2011 these are 45.99% using the first criterion and 64.52% using the second criterion for the MACD momentum rule and 48.64% and 70.72% for the MACD vs. signal rule. Also, more importantly, the average cost and risk adjusted excess returns is positive and statistically significant for both years and both rules, while the average P1 probabilities are significantly higher than 50% and clearly reject the EMH with a p-value of 0.0000 in all cases. This means that in those two years, investors could have used both MACD rules in order to obtain substantial cost and risk adjusted excess returns. By using the previously explained approach of ranking by relative efficiency, it can be seen that the post-crisis (post 2007) efficiency of all markets in the CEE region has declined when compared with the pre-crisis period. Table 2 shows that from the 6 post-crisis years, 5 are ranked in the bottom half of the ranking, with 2011 and, especially, 2008 being the least efficient, with only 2009 being in the top half of the ranking. The results are very similar with Anghel (2013b) when using the RSI indicator for with CEE countries. This shows the negative effect that significant market crises can have of informational efficiency on world stock markets. The reasons for why this happens would be a very interesting research subject, with the author's money being placed on a deteriorated investor base that the crises generated. In other words, the

smarter (which are in general big, institutional and, more importantly, foreign of the region) investors left these markets to seek risk protection on more liquid ones, leaving only the smaller and less rational investors to trade here. Whatever the causes, the results indicate this phenomenon.

Table 2. Relative efficiency by year

Year	Ranking using RSI trend-following rule	Ranking using RSI contrarian rule	Overall Ranking
2005	1	1	1
2003	2	2	1
2004	3	3	1
2009	4	4	4
2006	5	5	5
2010	6	6	6
2012	7	7	7
2007	8	8	8
2002	9	9	9
2011	10	10	10
2008	11	11	11

Overall, when looking at the results, it seems that the efficiency properties of stock markets should be viewed more like a relative concept and not a static one. Further, the heterogeneity of results and the fact that there are some cases for which abnormal profit opportunities exist mean that the level of information incorporation into stock prices vary both in time and from market to market. At first glance this leads to the overall acceptance of the Adaptive Market Hypothesis of Lo (2004), rather than the EMH, for the stock markets of the world. However, this statement should be viewed with much care, because the rejection of the EMH for the years 2008 and 2011 is not so evident, even though the provided data supports this idea. In the spirit of Timmerman and Granger (2004), several questions should be asked and resolved before ruling out informational efficiency:

- Did investors pose the presented methods, estimation techniques and research technologies in order to use them and to profit from the information they provided? Because the MACD is widely used and there are several software providers that incorporate rule optimization into their trading simulation software, the answer to this question is that they clearly existed and they could have been used by actual investors in the markets, but there is no way of knowing if this investment technique has actually been used in practice.
- Have all trading costs and market restrictions been taken into account? For the market restrictions the answer is “Yes”, but for the trading cost the answer is still “No”. Although a huge step has been made in this paper with the incorporation of liquidity-related costs, the same thing could not be done for research costs and trade impact costs. As the answer to the first question indicates, in order to fully profit from this trading strategy, a trader must invest in some specialized software, or, at least, build his own, this requiring additional research and/or learning costs. This category of trading costs is almost impossible to evaluate and they were not evaluated here. The same goes for the cost generated by the impact of new orders in the market.

- How would a trader know ex-ante when to use this trading strategy? When looking at the yearly profitability evolution, it is not clear how an investor would have known at the beginning of 2008 and 2011 that the next year would be a successful year for RSI-based trading strategies, given that the results in prior years were not satisfactory. An intuitive link could be made to the crises and the pronounced bear markets that it generated specifically in these years. If an investor could have somehow guessed that the crises could have such a pronounced effect on market efficiency, then he would have considered using technical analysis investment methods. Maybe this is possible using state of the art estimation techniques and lots of financial flair, but in the author's opinion it is a very unlikely scenario for an average investor. So the question remaining is: Are the 2008 and 2011 detected anomalies a sign of market inefficiency or remain just market inconsistencies. If the answer is that they are just passing inconsistencies, than the definitive conclusion of the paper is that of accepting the weak form EMH for the studied CEE countries. But if someone could prove otherwise, than the only explanation is the AMH. Because no definite proof can be provided to state that the detected anomalies are indeed inefficiencies, this paper supports the EMH for the studied countries on a timely bases (but note on a country-by-country basis).

In a nutshell, the results presented in this paper show that weak form efficiency can be discarded for 34 of the 75 studied markets, when applying Appel's MACD as an investment technique. Besides this, this paper provides a ranking of relative market efficiency of the studied national stock markets. When looking at temporal results, important anomalies are detected for two post-crises years, but this is not proof enough to support the Adaptive Market Hypothesis, rather it is proof that the crises had a negative effect on weak form efficiency in a relative form.

5. Conclusions

This paper evaluates the weak form market efficiency of the stock markets of 75 countries of the world, starting with January 1, 2001 and up to December 31, 2012, by evaluating the economic relevance of the Moving Average Convergence Divergence, a very popular technical analysis indicator developed by Gerard Appel in the 1970's. Two separate trading rules derived from the MACD are tested: a simple momentum rule (long if MACD is higher than zero) and an MACD vs. signal rule (buy if MACD is higher than its signal line). The paper is relevant for both researchers and practitioners because it tries to answer three basic questions regarding the MACD: Is it capable of generating excess economic returns when applied to stock markets? Does it have any value for an investor that trades on stock markets? How can the stock markets of the world be characterized from an informational efficiency point of view?

Many papers that evaluate market efficiency have been written to date. This paper contributes to the international body of knowledge in three ways: first, the trading simulation is improved by incorporating all measurable trading costs that an investor encounters when he/she is active in the market; second, a different return indicator is used as the target optimization measurement; third, the amount of data used and also its quality are a big plus versus the majority of existing papers. Here, 1268 companies from 75 different countries are studied. Also, this paper tries to correct on existing methodological problems through using a testing techniques inspired by Timmerman and Granger (2004), which can be considered a guide for anyone trying to write on this topic. The methodology is based on the Standard and Bootstrap methods, as described by Park and Irwin (2007), but here the following improvements have been implemented: (*) the returns are adjusted to risk, by using the geometric M2 for Sortino excess return as the target optimization measurement; (*) the returns are adjusted to all observable direct trading costs; (*) the trading simulation procedure is improved in order to account for the unobservable costs induced by liquidity risk; (*) two non-standard bootstrap based tests are applied in order to statistically evaluate the results in all trading windows; (*) shorter data windows are used in order to mimic even closer what investors actually do in practice; (*) only long trades are implemented. The

same procedure has also been used by Anghel (2013a) when analyzing the performances of the Rate of Change indicator on the Romanian Stock Market and Anghel (2013b) when studying market efficiency in the CEE region using the RSI. Although several vulnerabilities can still be identified in the methodology, a consistent step has been made in the right direction.

The results vary greatly for both MACD implemented rules at the individual company level. There are numerous examples for which the MACD managed to obtain significant positive cost and risk adjusted returns. Overall, the null hypothesis of economically relevance for both studied rules is rejected using all available criteria, this meaning that the EMH cannot be rejected at a general level for the world stock markets using the MACD as a trading method. But this only means that this specific indicator is not applicable at the general level. In a country-by-country analysis, 34 inefficient markets are detected. By aggregating the result, a relative efficiency hierarchy can be established, with Colombia, Australia and Austria being the most efficient, while Serbia, Vietnam and Ukraine being the least efficient.

When examining temporal results, some indication exist that the crises has had a negative effect on market efficiency. Also, four significant anomalies are detected: both rules are able to generate significant cost and risk adjusted excess returns in 2008 and 2011. But when looking at the big picture, it is not clear how an investor would have known ex-ante (at the beginning of 2008 and 2011) that the next year would be a successful year for RSI-based trading strategies, given that the results in prior years were not satisfactory. This leads to the conclusion that the detected anomalies are cannot truly be considered inefficiencies. Thus, in the end, the evidence provided is not sufficient to reject the EMH and accept the AMH on a temporal basis.

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