European Research Studies
Volume IX, Issue (3-4), 2006

Testing Technical Anomalies in Athens Stock Exchange (ASE)

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Abstract

The purpose of this paper is to investigate the existence of historical Market anomalies in the Athens Stock Market (ASE). The market anomalies that are going to be explored are technical ones concerning the trading rules of the various types of moving averages.

The above anomalies were observed in most developed and developing markets. This study will investigate these effects for the most important index of the Athens market, the Athens General Index. The data used are for the period from 1/1/1990 to 31/12/2004. Overall, our results confirm the existence of technical anomalies in ASE and provide strong support for profitability of those technical trading rules.

Keywords: Stock markets, technical anomalies, bootstrap.

JEL classification: G12, G15.

1. Introduction

Basic aim of this paper is to investigate the existence of market anomalies in the Athens Exchange Market and particularly for the General Index of ASE (Athens Stock Exchange). The market anomalies that are going to be explored are technical anomalies concerning the trading rules of the simple moving average and the exponential moving average.

Technical Analysis is the study of prices with charts being the primary tool to make better investments. Otherwise, technical analysis tests historical data attempting to establish specific rules for buying and selling securities with the objective of maximising profits and minimising risk of loss. Basic idea of technical analysis is to forecast the equity prices examining past prices.

Technical anomalies were observed in most developed and developing markets. Although many earlier studies concluded that technical analysis is useless, the recent studies on predictability of equity returns from past returns suggest that this conclusion might have been premature. This paper will sum up these anomalies that seem to contradict with the evidences that the stock markets are highly efficient. It is the

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Efficient Market Hypothesis and random walk theory versus practice. This study will investigate technical anomalies for the most important index of the Athens market, the Athens General Index. The Athens General Index is the most famous index of the Athens Exchange.

In this paper, we explore two of the simplest and most popular technical rules: simple moving averages and the exponential moving averages. These rules will be evaluated by their ability to forecast future price changes. The methodology that is going to be used for the analysis of the data is standard tests (t-test), which was used in the past in numerous studies for the investigation of technical anomalies. The t-test is used in order to assess if the means of two data groups are statistically different from each other in order to compare these means. The t-test formula is a ratio. In addition, standard tests will be compared with the bootstrap methodology inspired by Efron (1979), and Efron and Tibshirani (1986). Bootstrapping is a method, introduced by Efron (1979), for estimating the distributions of statistics that are otherwise difficult or impossible to determine. The general idea behind the bootstrap is to use resampling to estimate an empirical distribution for the statistic. Artificial samples are drawn from the original data, being the statistic of interest recalculated based on each artificial sample. The resulting "bootstrapped" measures are then used to construct a sampling distribution for the statistic of interest. Following this methodology, returns from an artificial Athens Stock Exchange series are generated and the trading rules are applied to the series. Comparisons are then made between returns from these simulated series and the actual Athens Stock Exchange series.

In this paper there will be an investigation of the time periods from 1990 to 2004. The period 1990 - 2004 is a very important investigation period for the Athens Stock Exchange as there are no studies for that period, the Athens Stock exchange has become a developed market, Greece has adopted the euro currency and a successful derivatives market in introduced. In Greece there were no investigations concerning the technical anomalies. The majority of stock market professionals worldwide and in Athens Exchange use technical analysis. The moving average rule gives entry signals in the case the moving average of the short period penetrates the moving average of the long period. The short signal is given when the long period moving average penetrates the short period moving average.

In section 2 we see the literature review. This chapter refers to the available knowledge that is related to the topic of investigation. Section 3 describes the data and technical trading rules used. Section 4 reports the methodology of the paper. In section 4 we see the outcomes and findings of the research (standard statistical & empirical results from the bootstrap simulations). Finally, in section 5 the outcome and the concluding remarks of the research are stated and summarized.

2. Literature Review

Fama and French (1988) in tests for the 1926 to 1985 period examined autocorrelations of daily and weekly stock returns. They found significant statistical serial correlation in price series of small and large firm portfolios of all New York Stock Exchange stocks, over various time horizons. Their state"Our results add to mounting evidence that stock returns are predictable". They estimated that 25-45% of the variation of 3-5 year stock returns is predictable.

Neftci (1991) studied the usefulness of the well-defined rules of technical analysis are useful in prediction. The first of the two interests of the study were to devise formal algorithms to represent various forms of technical analysis and see if these rules are well defined. The second interest was to discuss the conditions that technical analysis can capture properties of stock prices by linear models of Wiener-Kolmogorov prediction theory. The author concludes, “Tests done using Dow-Jones industrials for 1911-76 suggested that this may indeed be the case for the moving average”.

Brock William, Lakonishok Josef, LeBaron Blake (1992), also known as (BLL), tested two of the simplest and most popular trading rules--moving average and trading range break--by utilizing the Dow Jones Index from 1897 to 1986. Standard statistical analysis is extended using bootstrap techniques. Overall, their results provide strong support for the technical strategies. The returns obtained from these strategies are not consistent with four popular null models: the random walk, the AR(1), the GARCH-M, and the Exponential GARCH. Buy signals consistently generate higher returns than sell signals, and further, the returns following buy signals are less volatile than returns following sell signals. Moreover, returns following sell signals are negative, which is not easily explained by any of the currently existing equilibrium models.

Balsara Nauzer, Carlson Kathleen and Narendar V. Rao, (1996), studied the behaviour of a fixed-parameter technical trading rule as applied to four commodity futures contracts. They used the dual moving average crossover rule to generate buy and sell signals. The evidence suggests that fixed-parameter rules are inflexible, leading to wide swings in performance both across commodities and across periods. They concluded, “These findings have powerful practical implications, in as much as they recommend that traders be wary about using fixed-parameter mechanical trading systems. Instead of expecting the market to adapt to a fixed, time-invariant set of rules, a mechanical system should be flexible in nature, adjusting its parameters dynamically in response to changes in market conditions as soon as they occur. Flexible systems are the key to success in any technical trading program in the futures market.”

Rodríguez, Sosvilla and Andrada (1999) in their paper judge whether some simple forms of technical analysis as Variable Moving Average, Fixed Moving Average and Trading Range Break out can predict stock price movements in the Madrid Stock Exchange. Their study covered the period from January 1966 to October 1997. They used the daily data of the General Index of the Madrid Stock Exchange and the bootstrap methodology. They state, “Our results provide strong support for profitability of these technical trading rules.”

Ki-Yeol Kwon and Richard J. Kish (2002) investigated an empirical analysis on technical trading rules (the simple price moving average, the momentum, and trading volume) utilizing the NYSE value-weighted index over the period 1962-1996. The methodologies employed include the traditional *t*-test and residual bootstrap methodology utilizing random walk, GARCH-M and GARCH-M with some instrument variables. The results indicate that the technical trading rules add a value to capture profit opportunities over a buy-hold strategy.

Wing-Keung Wong, Meher Manzur, Boon-Kiat Chew (2003) focuses on the role of technical analysis in signalling the timing of stock market entry and exit. Test statistics are introduced to test the performance of the most established of the trend followers, the Moving Average, and the most frequently used counter-trend indicator, the Relative Strength Index. Using Singapore data, the results indicate that the indicators can be used to generate significantly positive return. It is found that member firms of Singapore Stock Exchange (SES) tend to enjoy substantial profits by applying technical indicators.

Atmeh M. and Dobbs I.M., (2004) investigated the performance of moving average rule in the Jordanian stock market. The returns from trading strategies based on various moving average rules are examined. The results show that technical trading rules can help to predict market movements, and that there is some evidence that (short) rules may be profitable after allowing for transactions costs, although there are some caveats on this. Sensitivity analysis of the impact of transaction costs is conducted and standard statistical testing is extended using bootstrap techniques. The conditional returns on buy or sell signals from actual data are compared to the conditional returns from simulated series generated by a range of models (random walk with a drift, AR (1), and GARCH-(M)) and the consistency of the general index series with these processes is then examined.

3. Data and technical trading rules

In this study, we use data series for the General Index of Athens Stock Exchange from the 1/1/1990 to 31/12/2004. The database used is composed of 3734 observations. The Athens General Index is the most famous index of the Athens Exchange. The Athens General Index constituted from the 60 stocks of the Athens Exchange with the largest capitalization.

Moving averages are one of the oldest and most popular technical analysis tools. A Moving Average is an indicator that shows the average value of a security's price over a period of time. When calculating a moving average, you specify the time span to calculate the average price. According to the moving average rule, buy and sell signals are generated by two moving averages of the level of the index: a long-period average and a short-period average. A typical moving average trading rule prescribes a buy (sell) when the short-period moving average crosses the long-period moving average from below (above). The idea behind computing moving averages it to smooth out an otherwise volatile series. As can be seen, the moving average rule is essentially a trend following system because when prices are rising (falling), the short-period average tends to have larger (lower) values than the long-period average, signalling a long (short) position.

The only significant difference between the various types of moving averages is the weight assigned to the most recent data. Simple moving averages apply equal weight to the prices. Exponential and weighted averages apply more weight to recent prices.

The critical element in a moving average is the number of time periods used in calculating the average. The most popular moving average is the 30-day moving average. This moving average has an excellent track record in timing the major market cycles. These moving averages are used in this paper, as they are the most common in used by the chartists-technical analysts.

Adding the closing price of the security for a number of time periods and then dividing this total by the number of time periods calculates a simple moving average. The result is the average price of the security over the time period. Simple moving averages give equal weight to each daily price.

An exponential moving average is calculated by applying a percentage of today's closing price to yesterday's moving average value. Exponential moving averages place more weight on recent prices.

We evaluate the following popular moving average rules: 1-9, 1-15, 1-30, 1-50 and 1-90, where the first number in each pair indicates the days in the short period and the second number shows the days in the long period.

All transactions assume 0.18% (of the investing capital) commission as entry (buy) fees and 0.31% (of the investing capital) as exit (sell) fee. Those fees are usual fort institutional investors or securities firms participate in these transactions.

4. Methodology

In this section, there is a description of the research objective of this project and the rationale behind it. The research objective of this project is to investigate the existence of technical anomalies in the Athens exchange market.

The technical anomalies that are going to be investigated are simple moving averages and exponential moving averages. The investigation of these moving averages will be achieved by comparing the returns given by the buy (long position) signals of the moving average with the returns of the buy and hold method. Furthermore, the returns given by the buy signals of the moving average minus the returns of the sell signals of the moving average with the returns of the buy and hold method will be compared. The hypothesis that the returns of the buy and hold method with the returns of the moving average method will be examined using the t-test methodology. The moving averages give buy signal when the short term moving average crossover the long-term moving average. On the other side, we have a sell signal when the long term moving average crossover the short-term moving average.

Before the investigation of the technical anomalies, using the t-test, descriptive statistics will be used. The use of descriptive statistics is a common first step in order to summarize, organize and describe the information of the data, in this case the returns of the indices. A way to measure the central tendency of the information is by calculating the mean return. The mean return is calculated adding the daily returns of an index, for a period, dividing the sum by the total number of observations for that period.

As we told the methodology that is going to be used for the analysis of the data is t-test, which was used in the past in numerous studies for the investigation of technical anomalies. The t-test is used in order to assess if the means of two data groups are statistically different from each other in order to compare these means. The t-test formula is a ratio.

The t-statistic is calculated by the formula:

$$t = \frac{\overline{R_1} - \overline{R_2}}{\sqrt{\left(\frac{SD_1^2}{N_1} + \frac{SD_2^2}{N_2}\right)}}$$

Where the:

SD_1 is the square root of the variance of the returns of the case 1.

SD_2 is the square root of the variance of the returns of the case 2.

N_1 is the number of measurements considered of the case 1.
N_2 is the number of measurements considered of the case 2.
$\overline{R}_1$ is the mean daily returns of the index of the case 1.
$\overline{R}_2$ is the mean daily returns of the index of the case 2.

Finally, the t-test will be used in the moving average case. Using t-test will compare the mean returns of the unconditional buy methodology with the returns of the buy signals given by the moving averages and the returns of the unconditional buy methodology with the returns of the buy signals minus the returns of the sell signals given by the moving averages.

The results of the t-test will help to either accept the null hypothesis (there is no actual difference between mean returns) or reject our null hypothesis (there is an actual difference the mean returns). So the two hypotheses for the above test are:

Accept Null Hypothesis: $H_1 : \overline{R_1} - \overline{R_2} = 0$

Reject Null Hypothesis: $H_2 : \overline{R_1} - \overline{R_2} \neq 0$

All transactions assume 0.18% (of the investing capital) commission as entry (buy) fees and 0.31% (of the investing capital) as exit (sell) fee. Those fees are usual fort institutional investors or securities firms participate in these transactions.

The results presented in t test assume independent, stationary and asymptotically normal distributions. Many times these assumptions certainly do not characterize the returns from the ASE series. Following BLL (1992), this problem can be solved using bootstrap methods (Efron and Tibshiarani, 1993).

Bootstrapping is a method, introduced by Efron (1979), for estimating the distributions of statistics that are otherwise difficult or impossible to determine. The general idea behind the bootstrap is to use resampling to estimate an empirical distribution for the statistic. Artificial samples are drawn from the original data, being the statistic of interest recalculated on the basis of each artificial sample. The resulting "bootstrapped" measures are then used to construct a sampling distribution for the statistic of interest.

The Procedures of the bootstrap method is: creating Z bootstrap samples, each consisting of N observations by sampling with replacement from the original return series. Then we calculate the corresponding price series for each bootstrap sample given that the price next period is

$$P_{t+1} = exp(r_{t+1})P_t$$

After that we apply the trading rule (moving average) to each of the Z pseudo price series. Afterwards, we calculate the performance statistic of interest for each of the pseudo price series. Finally we determine the P-value by calculating the number of times the statistic from the pseudo series exceed the statistic from the original price series. To use the bootstrap method a data generating process (DGP) for market prices or returns must be specified a priori. The bootstrap method can be used to generate many different return series by sampling with replacement from the original return series.

The bootstrap samples created are pseudo return series that retain all the distributional properties of the original series, but are purged of any serial dependence. Each bootstrap sample also has the property that the DGP of prices is a random walk with drift.

$$\ln P_{t+1} = \mu + \ln P_t + \varepsilon_t$$
$$\varepsilon_t \sim IID\ N(0, \sigma^2)$$

Where μ represents the drift in the series, $\ln P$ is the natural logarithm of the price and ε is the stochastic component of the DGP.
To test the significance of the trading rule excess returns the following hypothesis can be stated

$$H_0 : \quad XR \leq \bar{X}\bar{R}^*$$
$$H_1 : \quad XR > \bar{X}\bar{R}^*.$$

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Under the null hypothesis, the trading rule excess return (XR) calculated from the original series is less than or equal to the average trading rule return for the pseudo data samples ($\bar{X}\bar{R}^*$).

The p-values from the bootstrap procedure are then used to determine whether the trading rule excess returns are significantly greater than the average trading rule return given that the true DGP is a random walk with drift.

In order to test our hypothesis we will use the econometric program Matlab 7.0. The bootstrap methodology requires high computer power and computer programming (because there are not any toolboxes for bootstrapping suited for this study).

5. Findings

5.1 Standard statistical results

Table 1 reports some summary statistics for daily returns. Returns are calculated as log differences of the General Index of ASE level. As can be seen, these returns exhibit excessive kurtosis and nonnormality in returns.

Table 1 Statistics for daily returns

num:	3733
max:	0.1375
min:	-0.0962
mean:	0.000482112
median:	-0.000727175
range:	0.2336
std:	0.0176
skewness:	0.2102
kurtosis:	7.8903
jarquebera:	0.000374523
jbpval:	0

Descriptive Statistics for the returns
Jarque-Bera test for Normality
JB-stat p-value
------- ------
0.000374523 0.000000 rejects Normality
Buy-Hold mean return 0.000482112 euro equity

Returns are calculated as log differences of the General Index of ASE level.

If technical analysis does not have any power to forecast price movements, then we should observe that returns on days when the rules emit by signals do not differ appreciably from returns on days when the rules emit sell signals.

In Table 2 we present the results from simple moving average trading strategies. The rules differ by the length of the short and long period. For example (1,50) indicates that the short period is one day, the long period is 50 days. We present results for the 6 rules that we examined. In 3 and 4 columns (table 2) we report the number of buy "N(Buy)" and sell "N(Sell)" signals generated during the period. When we write about buy we discuss for long position [we begin the transaction with buy position and then we sell – we follow long position in (bull) up-trend market]. On the other hand when we write about sell we discuss for short position [we begin the transaction with sell position and then we buy – we follow short position in (bear) down-trend market]. The (daily) mean buy and sell returns are reported separately in columns 5 and 6. The last column "Buy-Sell" lists the differences between the mean daily buy and sell returns. The t statistics for the Buy and Sell statistics are computed using the following BLL, 1992 methodology.

Table 2: Standard results for the simple moving rules						
Period	Test	N(buy) (Long Strategy)	N(sell) (Short Strategy)	Buy (Long Strategy)	Sell (Short Strategy)	Buy-sell
1/1/90 to	(1,9)	273	272	0.001168	-0.00074	0.001906
31/12/04	(1,15)	202	201	(2.992496)	(-3.6324)	(6.440012)
	(1,21)	161	160	0.001081	-0.00066	0.001737
	(1,30)	128	127	(2.911536)	(-3.36109)	(6.062579)
	(1,50)	87	86	0.000956	-0.00054	0.001497
	(1,90)	62	61	(2.44205)	(-3.04905)	(5.219619)
	Average			0.00961	-0.00056	0.001521
				(2.43062)	(-3.10043)	(5.305773)
				0.000725	-0.00038	0.001108
				(2.015469)	(-2.58049)	(3.890203)
				0.000576	-0.00032	0.000896
				(1.358212)	(-2.38927)	(3.199685)
				0.000911	-0.000533	0.001444
Notes: N(buy) and N(Sell) are the number of buy and sells signals generated by the rule. Number in parentheses are standard t-statistics testing the difference, respectively, between the mean buy return and the unconditional mean return, the mean sell return and the unconditional mean return, and buy-sell and zero. The last row reports averages across all 6 rules.						

As we can see in Table 2, the buy-sell differences are significantly positive for all rules. All the buy-sell differences are positive and the t-tests for these differences are highly significant rejecting the null hypothesis of equality with zero. [For 0.05 probability the upper (lower) critical values of the t-test values are +(-) 1.960]. The mean buy-sell returns (short – long position) are all positive with an average daily return of 0.1444 percent, which is about 36.10 percent at an annual rate (250 trading days x 0.1444%).

We present results for the 6 rules that we examined. The mean buy returns (long position) are all positive with an average daily return of 0.0911 percent, which is about 22.78 percent at an annual rate (250 trading days x 0.0911%). The t-statistics reject the null hypothesis that the returns equal the unconditional returns (0.048 percent from Table 1). Five of the six tests reject the null hypothesis that the returns equal the unconditional returns at the 5 percent significance level using a two-tailed test. The other five tests are significant. For the sells (short position), the average daily return of 0.0533 percent, which is 13.32 percent on an annualised basis. All of the tests reject the null hypothesis that the returns equal the unconditional returns at the 5 percent significance level using a two-tailed test. Under the null hypothesis that technical rules do not produce useful signals the fraction of positive returns should be the same for both buys and sells.

The lowest number of buy signals is for the (1,90) rule which generates an average of 4.43 signals per year over the 14 years of data. Also, the largest number of buy signals is generated by the (1,9) rule with 19.5 signals per year.

The largest number of sell signals is for the (1,9) rule which generates an average of 19.43 signals per year over the 14 years of data. Also, the lowest number of buy signals is generated by the (1,90) rule with 4.36 signals per year

In Table 3 we display the results from exponential moving average trading strategies. The rules differ by the length of the short and long period. We present results for the 6 rules that we examined. In 3 and 4 column (table 2) we report the number of buy "N(Buy)" and sell "N(Sell)" signals generated during the period. The mean buy and sell returns are reported separately in columns 5 and 6. The last column "Buy-Sell" lists the differences between the mean daily buy and sell returns. The t statistics for the Buy and Sell statistics are computed using the following BLL, 1992 methodology.

Table 3: Standard results for the exponential moving rules

Period	Test	N(buy) (Long Strategy)	N(sell) (Short Strategy)	Buy (Long Strategy)	Sell (Short Strategy)	Buy-sell
1/1/90 to	(1,9)	145	144	0.000964	-0.00053	0.001497
31/12/04	(1,15)	99	98	(2.568305)	(-3.0221)	(5.218606)
	(1,21)	84	83	0.001019	-0.0059	0.001612
	(1,30)	66	65	(2.627126)	(-3.21687)	(5.62262)
	(1,50)	36	35	0.000736	-0.00032	0.001057
	(1,90)	30	29	(2.540766)	(-2.39801)	(3.678029)
	Average			0.000722	-0.00032	0.001041
				(2.398905)	(-2.39088)	(3.625273)
				0.000618	-0.00028	0.000894
				(2.283028)	(-2.27566)	(3.133622)
				0.000307	-0.00005295	0.000360
				(1.45634)	(-1.62567)	(1.28446)
				0.000728	-0.000349	0.0010767

Notes: N(buy) and N(Sell) are the number of buy and sells signals generated by the rule. Number in parentheses are standard t-statistics testing the difference, respectively, between the mean buy return and the unconditional mean return, the mean sell return and the unconditional mean return, and buy-sell and zero. The last row reports averages across all 6 rules.

As we can see in Table 3, the buy-sell differences are significantly positive for all rules. All the buy-sell differences are positive and the t-tests, except one, for these differences are highly significant rejecting the null hypothesis of equality with zero.[For 0.05 probability the upper (lower) critical values of the t-test values are +(-) 1.960]. The mean buy-sell returns (short – long position) are positive with an average daily return of 0.1077 percent, which is about 26.92 percent at an annual rate (250 trading days x 0.1077).

The mean buy returns (long position) are all positive with an average daily return of 0.0728 percent, which is about 18.19 percent at an annual rate (250 trading days x 0.0728%). All except one t-statistics reject the null hypothesis that the returns equal the unconditional returns (0.048 percent from Table 1). For the sells (short position), average daily return of 0.0349 percent, which is 8.73 percent on an annualised basis. All except one of the tests reject the null hypothesis that the returns equal the unconditional returns at the 5 percent significance level using a two-tailed test.

The lowest number of buy signals is for the (1,90) rule which generates an average of 2.14 signals per year over the 14 years of data. Also, the largest number of buy signals is generated by the (1,9) rule with 10.36 signals per year.

The largest number of sell signals is for the (1,9) rule which generates an average of 10.28 signals per year over the 14 years of data. Also, the lowest number of buy signals is generated by the (1,90) rule with 2.07 signals per year.

If we compare table 2 and table 3 we will see that the mean (buy) returns daily from simple moving averages are higher than mean buy returns from exponential moving averages (0.0911% >0.0728%). Also, the mean (sell) returns daily from simple moving averages are higher than mean sell returns from exponential moving averages (0.0533% >0.0349%). In addition the buy-sell mean returns daily from simple moving averages are higher than returns from exponential moving averages (0.1444% >0.1077%). Possible explanation is that simple moving averages give equal weight to each daily price while exponential moving averages place more weight on recent prices. Besides the last five years we have lived in down trend market. Both of technical strategies “beat” or “win” the market (General Index of Athens Stock Exchange – Buy and hold Strategy). In particular, Buy-Hold Strategy (Table 1) give us 12 % per year (0.048 X 250 days) and using exponential moving averages strategy 26.92 % (buy-sell) at an annual rate and using simple moving averages strategy 36.10 percent (buy-sell) at an annual rate.

a. Bootstrap Results

As we told t test assume normal, stationary, and time-independent distributions. For stock returns there are several well-known deviations from this assumed distribution. As we saw many distributions have positive or negative skewness values, which mean that distributions are skewed right or left. Also most of the distributions have positive Kurtosis values, which indicate that most of the return distributions are leptokurtic. So we further our analysis via the bootstrap methodology under the null model of random walk with drift. Using the bootstrap methodology we enrich our analysis.

Bootstrap methodology inspired by Efron (1982), Freedman (1984), Freedman and Peters (1984a, 1984b), and Efron and Tibshirani (1986).
Following BLL we create 500 bootstrap samples, each consisting of 3734 observations by sampling with replacement from the original return series. Then we calculate the corresponding price series for each bootstrap sample. After that we apply the trading rule (moving averages) to each of the 500 pseudo price series. Afterwards, we calculate the performance statistic of interest for each of the pseudo price series. Finally we determine the P-value by calculating the number of times the statistic from the pseudo series exceed the statistic from the original price series (General Index).

So, each of the simulations is based on 500 replications of the null model (random walk with drift). This should provide a good approximation of the return distribution under the null model. The null hypothesis is rejected if returns obtained from the actual General index of ASE data are greater than the returns of the simulated returns under the null model.

In Table 4 we present the results of random walk simulations using simple moving average trading strategies via bootstrapping. The rules differ by the length of the short and long period. We present results for the 6 rules that we examined. All the numbers presented in 4, 5, 6 columns are the fractions of the simulated result which are larger than the results for the original General index of Athens Stock Exchange. The mean buy and sell returns are reported separately in columns 4 and 5. Results for returns are presented in the columns 4,5,6 are p-values. The p-values from the bootstrap procedure are then used to determine whether the trading rule excess returns (simple moving averages) are significantly greater than the average trading rule return given from original series. The numbers in parenthesis in 4,5,6 columns show how many series from 500 replications are greater than from original returns. More specifically the number in the column labelled Buy, which is (428), shows that 428 of the simulated random walks generated a mean buy return as large as that from the original General index of Athens Stock Exchange. As we see from reported numbers in 4,5,6 columns most of the simulated random walks were greater than those from the General index of Athens Stock Exchange series. All the buy, sell and buy-sell are highly significant accepting the null hypothesis. Under the null hypothesis, the trading rule excess return (XR) calculated from the original series is less than or equal to the average trading rule return for the pseudo data samples ($\bar{XR}^*$). [For 0.05 probability the p-value must be greater than 0.05 (p-value>0.05). The results for the returns are consistent with the traditional tests presented earlier.

Table 4: Simulation Tests from Random Walk Bootstraps for 500 replications (simple moving rules)

Period	Test	Results	Buy	Sell	Buy-sell
1/1/90 to	(1,9)	Fraction > General Index	0.856	0.824	0.52
31/12/04			(428)	(412)	(260)
	(1,15)	Fraction > General Index	0.874 (437)	0.824 (412)	0.538 (269)
	(1,21)	Fraction > General Index	0.846 (423)	0.872 (436)	0.516 (258)
	(1,30)	Fraction > General Index	0.874 (437)	0.854 (427)	0.546 (273)
	(1,50)	Fraction > General Index	0.862 (431)	0.86 (430)	0.554 (277)
	(1,90)	Fraction > General Index	0.848 (424)	0.846 (423)	0.58 (290)
	Average		0.86	0.847	0.542

In Table 5 we present the results of random walk simulations using exponential moving average trading strategies. All the numbers presented in 4,5,6 columns are the fractions of the simulated result which are larger than the results for the original General index of Athens Stock Exchange. Results for returns are presented in the columns 4,5,6 are p-values. The number in parenthesis in 4,5,6 columns show how many series from 500 replications have greater returns than from original returns. All the buy, sell and buy-sell are highly significant accepting the null hypothesis. Under the null hypothesis, the trading rule excess return (XR) calculated from the original series is less than or equal to the average trading rule return for the

pseudo data samples ($\bar{X}R^*$). [For 0.05 probability the p-value must be greater than 0.05 (p-value>0.05).
Furthermore, it should be mentioned that the results are consistent with study of BLL (1992).

Table 5: Simulation Tests from Random Walk Bootstraps for 500 replications (exponential moving rules)

Period	Test	Results	Buy	Sell	Buy-sell
1/1/90 to	(1,9)	Fraction > General Index	0.846	0.842	0.512
31/12/04			(423)	(421)	(256)
	(1,15)	Fraction > General Index	0.848	0.856	0.558
			(424)	(428)	(278)
	(1,21)	Fraction > General Index	0.862	0.852	0.572
			(431)	(426)	(286)
	(1,30)	Fraction > General Index	0.872	0.88	0.588
			(436)	(440)	(294)
	(1,50)	Fraction > General Index	0.868	0.866	0.606
			(434)	(433)	(303)
	(1,90)	Fraction > General Index	0.858	0.876	0.64
			(429)	(438)	(320)
	Average		0.859	0.862	0.579

6. Conclusion.

In this paper, we have investigated of the existence of market anomalies in the Athens Exchange Market and particularly for the General Index of ASE (Athens Stock Exchange). The market anomalies that we have explored were technical anomalies (rules of simple moving averages and the exponential moving averages). The moving average rule gives entry signals in the case the moving average of the short period penetrates the moving average of the long period.

The rules of simple moving averages and the exponential moving averages have evaluated for the General Index of the Athens Stock Exchange (ASE), using daily data for the period from 1990 to 2004. This period was a very important investigation period for the Athens Stock Exchange as there are no studies for that period, the Athens Stock exchange has become a developed market, Greece has adopted the euro currency and a successful derivatives market in introduced. In Greece there were no investigations concerning the technical anomalies.

In our analysis, we have used standards tests in combination with bootstrap methods. The bootstrap methodology requires high computer power and computer programming because none econometric program has toolboxes for bootstrapping.

We evaluate the following popular moving averages rules: 1-9, 1-15, 1-30, 1-50 and 1-90, where the first number in each pair indicates the days in the short period and the second number shows the days in the long period. These moving averages are used in this paper, as they are the most common used by the chartists-technical analysts. In order to test our hypothesis we used the econometric program Matlab 7.0. The bootstrap methodology requires high computer power and computer programming (because there are not any toolboxes for bootstrapping). All transactions assume 0.18% (of the investing capital) commission as entry (buy) fees and 0.31% (of the investing capital) as exit (sell) fee. Those fees are usual fort institutional investors or securities firms participate in these transactions.

For the simple moving averages, trading strategies all the buy-sell differences are positive and the t-tests for these differences are highly significant rejecting the null hypothesis of equality with zero. The mean buy-sell returns (short – long position) are all positive with an average daily return of 0.1444 percent, which is about 36.10 percent at an annual rate. The mean buy returns (long position) are all positive with an average daily return of 0.0911 percent, which is about 22.78 percent at an annual rate. For the sells (short position), the average daily return of 0.0533 percent, this is 13.32 percent on an annualised basis. All of the tests reject the null hypothesis. Under the null hypothesis that technical rules do not produce useful signals the fraction of positive returns should be the same for both buys and sells.

For the exponential moving averages, trading strategies all the buy-sell differences are positive and the t-tests, except one, for these differences are highly significant rejecting the null hypothesis of equality with zero. The mean buy-sell returns (short – long position) are positive with an average daily return of 0.1077 percent, which is about 26.92 percent at an annual rate. The mean buy returns (long position) are all positive with an average daily return of 0.0728 percent, which is about 18.19 percent at an annual rate. For the sells (short position), average daily return of 0.0349 percent, this responds to 8.73 percent on an annualised basis.

Furthermore, both of technical strategies "beat" the market (General Index of Athens Stock Exchange – Buy and hold Strategy). In particular, Buy-Hold Strategy give us 12 % annually returns (0.048 X 250 days) and using exponential moving averages strategy 26.92 % (buy-sell) (at an annual rate) and using simple moving averages strategy 36.10 percent (buy-sell) at an annual rate.

These results seem to contradict with the Efficient Market hypothesis as the investors can gain abnormal returns investing in the effects of the market.

Overall, our results confirm the existence of technical anomalies in ASE, provide strong support for profitability of those technical trading rules, and are in general consistent with those previously reported papers.

References

1. Achelis Steven (1996). Technical Analysis from A to Z, IRWIN.
2. Atmeh M. and Dobbs I.M., (2004). "Technical Analysis and the stochastic properties of the Jordanian Stock Market Index Return", working paper.
3. Balsara Nauzer, Carlson Kathleen and Narendar V. Rao, (1996). “Unsystematic Futures Profits with Technical Trading Rules: A case for flexibility", Journal Of Financial And Strategic Decisions Volume 9 Number 1 Spring, pp 57-66.
4. Brown, D. P. and R. H. Jennings (1989). "On technical analysis", Review of Financial Studies 2, pp. 527-551.
5. Clyde, W. C. and C. L. Osler (1997). "Charting: Chaos theory in disguise?", Journal of Future Markets 17, pp. 489-514.
6. Efron, B. (1979). "Bootstrapping methods: Another look at the jacknife", Annals of Statistics 7, pp. 1-26.
7. Efron, B. and R. J. Tibshirani (1993). “An introduction to the bootstrap”, Chapman&Hall, New York.
8. Efron, B. (1982). The Jackknife, The Bootstrap, and Other Resampling Plans, Society for Industrial and Applied Mathematics, Philadelphia.
9. Efron, B.and R. Tibshirani, (1986). Bootstrap methods for standard errors, confidence intervals and other measures of statistical accuracy, Statistical Science 1, 54-77.
10. Fama E. and French K. (1988). “Permanent and Temporary Components of Stock Prices' Journal of Political Economy”, Volume 96, Issue 2, 246-274.
11. Fama E. (1965). “The Behaviour of Stock-Market Prices”, Journal of Business, Volume 38, Issue 1, 34-105.
12. Fama E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work, Journal of Finance, Volume 25, Issue 2, Papers and Proceedings of the Twenty-Eighth Annual Meeting of the American Finance Association New York, N.Y. December, 28-30, 383-417.
13. Fernandez-Rodriguez, F., Sosvilla-Rivero, S. and M. D. Garcia-Artiles (1997). "Using nearest neighbour predictors to forecast the Spanish stock market", Investigaciones Economicas 21, pp. 75-91.
14. Fernando Fernández-Rodríguez, SimóN Sosvilla-Rivero and Julián Andrada-Félix (1999). "Technical Analysis in the Madrid Stock Exchange", FEDEA – D.T.99-05, pp. 1-29.
15. Freedman, D., (1984). “On bootstrapping two-stage least squares estimates in stationary linear models”. Annals of Statistics 12, 827-842.
16. Freedman, D and S. Peters, (1984a). Bootstrapping a regression equation: Some empirical results, Journal of the American Statistical Society 79, 97-106.
17. Freedman, D (1984b). Bootstrapping an econometric model: Some empirical results, Journal of Business and Economic Statistics 2, 150-158.
18. Gençay, R. (1998). "The predictability of securities returns with simple technical rules", Journal of Empirical Finance 5, pp. 347-359.
19. Keim, Donald (1983). "Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence", Journal of Financial Economics, 12, pp 13-32.
20. Ki-Yeol Kwon and Richard J. Kish (2002). “Technical trading strategies and return predictability: NYSE”, Applied Financial Economics, Volume 12, Number 9 / September 01, pp 639 – 653.

21. Levich, R. and L. Thomas (1993). "The significance of technical trading rule profits in the foreign exchange market: A bootstrap approach", Journal of International Money and Finance 12, pp. 451-474.
22. Lyroudi, Subeniotis and Komisopoulos (2002). “Market anomalies in the A.S.E: the day of the week effect”.
23. Neftci S. (1991). “Naive Trading Rules in Financial Markets and Weiner-Kologorov Prediction Theory: A study of “Technical Analysis”. Journal of Business, Volume 64, Issue 4, 549-571.
24. P.-J. Detry and Philippe Gregoire, (2000). “Other evidences of the predictive power of technical analysis: the moving averages rules on European indexes”, CeReFiM, Belgium, pp 1-25.
25. Pring, M. J. (1991). “Technical analysis explained: The successful investor's guide to spotting investment trends and turning points”, McGraw-Hill, New York.
26. Reinganum, M. R. (1981). "Misspecification of Capital Asset Pricing: Empirical Anomalies Based on Earnings' Yields and Market Values", Journal of Financial Economics, 9, p.p. 19-46.
27. Taylor, M. P. and H. Allen (1992). "The use of technical analysis in the foreign exchange market", Journal of International Money and Finance 11, pp. 304-314.
28. William Brock, Josef Lakonishok and Blake LeBaron (1992). "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns", Journal of Finance, Vol. 47, No. 5, pp. 1731-1764.
29. Wing-Keung Wong, Meher Manzur, Boon-Kiat Chew (2003). “How rewarding is Technical analysis? Evidence from Singapore stock market”, Applied Financial Economics, Volume 13, Number 7 / July, pp 543 – 551.