BANK OF GREECE
EUROSYSTEM

Working Paper

Decomposing the predictive performance of the moving average trading rule of technical analysis: the contribution of linear and non linear dependencies in stock returns

Alexandros E. Milionis
Evangelia Papanagiotou

134

JULY 2011

BANK OF GREECE
Economic Research Department – Special Studies Division
21, E. Venizelos Avenue
GR-102 50 Athens
Tel: +30210-320 3610
Fax: +30210-320 2432

www.bankofgreece.gr

Printed in Athens, Greece
at the Bank of Greece Printing Works.

ISSN 1109-6691

DECOMPOSING THE PREDICTIVE PERFORMANCE OF THE MOVING AVERAGE TRADING RULE OF TECHNICAL ANALYSIS: THE CONTRIBUTION OF LINEAR AND NON LINEAR DEPENDENCIES IN STOCK RETURNS

Alexandros E. Milionis
Bank of Greece and University of the Aegean

Evangelia Papanagiotou
University of the Aegean

ABSTRACT

On several occasions technical analysis rules have been shown to have predictive power. The main purpose of this work is to decompose the predictive power of the moving average trading rule and isolate the portion that could be attributed to the possible exploitation of linear and non linear dependencies in stock returns. Data for the General Index of the Athens Stock Exchange are filtered using linear filters so that the resulting simulated "returns" exhibit no serial correlation. Applying moving average trading rules to both the original and the simulated indices and using a statistical testing procedure that takes into account the sensitivity of the performance of the trading rule as a function of moving average length, it is found that the predictive power of the trading rule is clearly weakened when applied to the simulated index indicating that a substantial part of the rule's predictive power is due to the exploitation of linear dependencies in stock returns. It is also found that the contribution of linear dependencies in stock returns to the performance of the trading rule is increased for shorter moving average lengths.

Key words: Market Efficiency, Technical Analysis, Moving Average Trading Rules, Athens Stock Exchange.

JEL classification: G14, G15, C2

Ackowledgements: The authors are grateful to H. Gibson for helpful comments. The views expressed in the paper are those of the authors and do not necessarily reflect those of the Bank of Greece.

Correspondence:
Alexandros E. Milionis
Bank of Greece,
Department of Statistics
21 E. Venizelos Avenue,
Athens, 102 50, Greece
Tel.: +30-210 3203855,
e-mail: amilionis@bankofgreece.gr

1. Introduction

As the theory of efficient markets indicates, in a weak-form efficient market, stock returns are not predictable and, hence, studying the time series of past stock prices to predict future price movements is useless (Fama, 1970; 1991). By contrast, the so-called technical analysis (i.e. the study of market action through the use of charts and a set of empirical rules set mainly by market practitioners for the purpose of forecasting future price trends) has been a thriving activity for more than a century (see Murphy (1986); Pring (1991) for a comprehensive treatment of technical analysis). Though many of these rules incorporate a good deal of subjectivity, Neftci (1991), using standard concepts from the theory of stochastic processes, showed that, in contrast to many rules employed by technical analysis, some technical rules are mathematically well defined.

Unquestionably among the rules of technical analysis which are mathematically well defined according to Neftci's (1991) argumentation the most celebrated is that of the moving average (MA). Although the MA trading rule may have several versions (see for instance Pring (1991)), the one employed most frequently is of the following form: at first two non-centred, moving averages with different length are created from the time series of stock prices:

$$MAL_t = \left(\frac{1}{N}\sum_{i=0}^{N-1}\gamma_i B^i P_t\right) \tag{1}$$

$$MAS_t = \left(\frac{1}{M}\sum_{i=0}^{M-1}\gamma_i B^i P_t\right) \text{ with N>M} \tag{2}$$

where MAL_t represents the relatively longer moving average with length N, calculated at time t, MAS_t represents the relatively shorter moving average with length M, P_t is the stock price at time t, γ_i are non-time varying parameters, and B is the backward shift operator, i.e. $B^i P_t = P_{t-i}$.

Buy signals are (sequentially) generated at the times τ_j^B, where:

$$\tau_j^B \equiv \inf\left\{t : t > \tau_j^B, MAL_t - MAS_t > DP_{t-1}\right\} \tag{3}$$

Sell signals are (sequentially) generated at the times τ_j^S, where:

$$\tau_j^S \equiv \inf \left\{ t : t > \tau_j^S , MAS_t - MAL_t > DP_{t-1} \right\} \tag{4}$$

where the initial times τ_0^B, τ_0^S are set equal to zero and *D* is the so-called "band" (a pre-specified non-negative constant).

The rule is based on one of the fundamental premises of technical analysis according to which prices move in trends and a trend in motion is more likely to continue than to reverse. A non-centered moving average will constantly underestimate (overestimate) prices if there is an upward (downward) trend in prices.

The MA rule has been used extensively by many researchers and for many capital and exchange rate markets (see for instance Brock *et al*. (1992); Hudson *et al*. (1996); Mills (1997); Kwon and Kish (2002); Cai *et al.* (2005); Olson (2004)). The general consensus is that the MA rule has predictive power, hence the hypothesis of weak form efficient markets is rejected, but this predictive power has fallen over recent years at least for the most developed capital markets (e.g. Bessembinder and Chan, 1998; Kwon and Kish, 2002; Cai *et al*., 2005).

In most of the published research work thus far, the predictive power of the moving average rule is statistically tested using specific combinations of the length of the shorter and the longer moving averages, which are selected in a rather arbitrary way; for instance the selection is based upon the popularity that some combinations of MA lengths enjoy among market analysts (e.g. Brock *et al*., 1992; Bessembinder and Chan, 1995; Fang and Xu, 2003). However, Milionis and Papanagiotou (2008a; 2008b; 2009) performed a sensitivity analysis of the performance of the trading rule and found that the series of cumulative returns corresponding to successive applications of the MA trading rule, where each time the value of the length of the longer moving average is increased by one, exhibit large variability and on several occasions these series were non-stationary or "near unit root". This means that either there is no specific level around which trading rule cumulative returns fluctuate, or there exist long swings away from a certain level. Further, they conclude that given the high variability of the performance of the MA trading rule as a function of the length of the longer MA, by just finding out that trading rules with some specific combinations of MA lengths can, or cannot, "beat the market" is not enough to allow safe conclusions to be drawn about the predictive power of the trading rule and, hence, about the validity of the hypothesis of weak form market efficiency. This observation makes it necessary to conduct some kind of sensitivity analysis, regarding trading rule returns, before any conclusion about the predictive power of the trading rule is drawn.

As is also argued in Neftci (1991), a necessary condition for the usefulness of technical analysis is the non-linearity of asset prices. If this condition holds, then by taking into consideration these non-linearities in an empirical way technical analysis may lead to profitable trading rules. In the recent years researchers started to use nonlinear methods to test for market efficiency and to compare their results with the moving average trading rule (for instance Fernandez-Rodriguez *et al*. (2003) showed that the nearest neighbour predictor performs better than the moving average trading rule).

This study aims to contribute to the literature on the predictive ability of moving average trading rule in several ways. More specifically: (i) a sensitivity analysis of trading rule cumulative returns is performed using not only original prices, but also simulated "prices" that may be derived by filtering the original prices using linear filters. This is important as such simulated prices, again for particular combinations of MA lengths that are chosen arbitrarily, are used by several researchers, who utilize bootstrapping techniques to test for the statistical significance of the predictive power of the trading rule (e.g. Brock *et al*., 1992; Bessembinder and Chan, 1995); (ii) a new innovative methodological approach for statistical inference regarding the predictive power of the moving average trading rule of technical analysis, based on sensitivity analysis is proposed and applied; (iii) the predictive performance of the MA trading rule is broken down into that part that can be attributed to linear interdependencies in asset returns and that part that is attributed to non-linearities; (iv) the possible existence of a functional relationship between the attenuation of the trading rule performance due to linear filtering and the length of the longer moving average is investigated. The rule is applied to daily closing prices of the General Index of the Athens Stock Exchange (ASE).

The rest of the paper is structured as follows: in section 2 we describe the data set and the Athens Stock Exchange; the methodology is explained in section 3; in section 4 we present and discuss the empirical results; section 5 concludes the paper.

2. The data and the market

The data set selected for this work are the daily closing prices of the General Index (henceforth GEN) of the Athens Stock Exchange for a period of twelve years from 27 April 1993 to 27 April 2005. The ASE until the late 1980s was a small isolated market, and investors were largely local. However, due to several reforms and the liberalization of capital flows, the participation of foreign institutional investors increased substantially and the ASE attracted the attention of financial analysts and fund managers (for further details see for instance Alexakis and Xanthakis (1995); Kavussanos and Dockery (2001); Milionis and Papanagiotou (2008a, 2008b, 2009); Panagiotidis (2009)). There is little doubt that during the period under consideration the most important event in terms of price movement in ASE was the speculative bubble that occurred around 1999 when the stock index price rose from about 2000 points in the beginning of 1998 to about 6400 points in September 1999 and back to less than 2000 points in 2002. That was indeed an exceptional period for the ASE. Although until December 1998 the number of investor shares (codes) were about 390,000 in December 1999 that number increased to about 1,500,000 codes (source: Athens Exchange Monthly Statistics Bulletin, 52)![1] Most of these codes belonged to naive and financially uneducated new investors. Their investment decisions were largely based not on any kind of financial analysis or professional advice, but on what they were told by their friends, relatives, or neighbours! Stock prices until September 1999 moved strongly upward deviating sharply from any fundamentals. Under such circumstances a collapse was inevitable and indeed thus far GEN has never again reached its peak of September 1999.

Apparently the situation just described is not supportive of the assumption that investors are rational and have homogeneous beliefs, which are essential preconditions for the efficient market hypothesis to hold. However, it is in such conditions that technical analysis may be most profitable as one of its fundamental premises, as mentioned earlier, is that market prices move in trends (see Murphy (1986); Pring

[1] In 1998 the Dematerialized Securities System (DSS) begun to operate in the ASE. All investors had to register with DSS by law. Some of the old investors did not register in 1998 but in 1999 (personal communication with the section of diffusion of information of the Athens Exchange); hence, the official number of new investors quoted in the Monthly Statistics Bulletin for 1999 comprise some of the old investors as well. This does not change the essence of our argumentation.

(1991)). As the so-called "smart money" precedes naive investors, such trends are understandable.

The whole time period is subdivided into three sub-periods:1993-1997, 1997-2001 and 2001-2005 (see Milionis and Papanagiotou (2008b) for a detailed justification). Each sub-period will be examined separately.

3. Methodology

As described in the introduction our first aim is to perform a sensitivity analysis of the cumulative returns of the trading rule when the latter is applied to both the original stock index and the simulated stock index The simulated stock index will be constructed by filtering out all linear interdependencies in index returns.

The existence and character of any linear dependencies in the series of GEN returns (the latter will be expressed as logarithmic differences of consecutive prices) may be revealed from the pattern of the sample autocorrelation and sample partial autocorrelation functions (ACF and PACF respectively). The sample ACF for the series of index returns (R_t), which is found to be stationary, is estimated as follows:

$$ACF(k) = \frac{\sum_{t=1}^{T-k}(R_t - \overline{R})(R_{t-k} - \overline{R})}{\sum_{t=1}^{T}(R_t - \overline{R})^2}$$

where k is the time lag and $\overline{R}$ is the mean return. The PACF at lag k is defined as the correlation between time series terms k lags apart, after the correlation due to intermediate terms has been removed. PACF provides further information (additional to that provided by the ACF) about the character of the linear serial correlation. The exact expression for the PACF is rather complicated and will not be presented here (see for example Box and Jenkins (1976)). Then, following the four-stage model-building methodology suggested by Box and Jenkins (1976), univariate models of the following form can be built to describe GEN returns for each time period:

$$\Phi(B)R_t = c + \Theta(B)\varepsilon_t$$

where: B is the so-called backward shift operator such that: $B^k R_t = R_{t-k}$;

$\Phi(B)=1-\varphi_1 B-\ldots-\varphi_p B^p$ is the autoregressive polynomial of order p with parameters $\varphi_1,\varphi_2,\ldots,\varphi_p$;

$\Theta(B)=1-\theta_1 B-\ldots-\theta_q B^q$ is the moving average polynomial of order q with parameters $\theta_1,\theta_2,\ldots,\theta_q$;

c is a non time varying parameter;

ε_t is a white noise process.

The residuals of such ARMA models will represent GEN "returns" free from any linear dependencies. Then, new simulated indices with autocorrelation-free returns can be constructed by considering the series ε_t of the residuals of the ARMA models instead of the true index returns, R_t.

Once these simulated indices for the total period and each sub-period are constructed, the sensitivity analysis of the MA trading rule cumulative returns will be applied to both the original and the simulated indices. More specifically, the shorter moving average will be kept equal to the series of stock index prices itself, the length of the longer moving average will vary from 5 to 100 (for the total time period the length of the longer moving average will vary from 5 to 150) with unit step[2], no filter will be used, i.e. the value of the parameter D in equations (3) and (4) will be set equal to one and all γ_i parameters in equations (1) and (2) will be also set equal to one. It is useful to perform such a sensitivity analysis for the cumulative trading rule returns on the original index, as Milionis and Papanagiotou (2008) point out, as a first step for the examination of the predictive power of the MA trading rule. A warning should be issued when the series of successive cumulative trading rule returns is found to be non-stationary. Henceforth the series of the successive cumulative trading rule returns derived from the original and the simulated indices will be denoted as G_L and S_L, respectively.

The second methodological issue has to do with the statistical testing procedure for the significance of the predictive power of the trading rule when the latter is applied to both the original and the simulated indices for each time period. So far, in most of the

[2] The length of 100 is a reasonable upper limit for the longer MA, as for the time period that the data cover above that level the total number of signals that the trading rule generates is very small.

research papers on the subject this is performed using the mean return of "sell" trading periods (i.e. the trading periods for which the capital should be liquidated, or sold short) to that of either the "buy" trading periods (i.e. the trading periods for which, according to the trading rule, the capital should remain invested in the market) or the mean return of the whole time span that the data (usually daily observations) cover. A *t*-test for these means cannot be legitimately applied, mainly due to the existence of autocorrelation, and, on many occasions, a bootstrap methodology is employed for significance testing (see Brock *et al*. (1992) for further details). However, as pointed out in the precious section, such an approach does not necessarily lead to a safe conclusion regarding the acceptance or not of weak form efficiency.

For this reason another approach to the statistical testing of the significance of the predictive power of the MA trading rule will be followed, in which the variability in the performance of the trading rule is taken into consideration. A crucial point for this methodology is to examine, whether or not, the series G_L is stationary. For those cases where G_L is not stationary, the conclusion about the statistical significance of the predictive power of the trading rule can be drawn at the qualitative level only. By contrast, for the cases where the series G_L are found to be stationary, cumulative trading rule returns will fluctuate around a certain level. However such a significance testing is not standard inasmuch as if successive cumulative trading rule returns are perceived as a sample, this sample is far from being random, as these cumulative returns are strongly interrelated. Hence, the well-known Sample Mean Theorem (e.g. Goldberger, 1991), which defines the standard error of the sample mean cannot be applied. In Appendix 1 we prove what we name as the "Augmented Sample Mean Theorem" according to which the sample mean m_{G_L} is an unbiased estimator of the population mean μ and the variance of the sample mean for our case is given by:

$$s_m^2 = \frac{\sigma^2}{\mathrm{N}}\left[1 + 2\frac{(\mathrm{N}-1)}{\mathrm{N}}\rho_1 + 2\frac{(\mathrm{N}-2)}{\mathrm{N}}\rho_2 + \ldots + \frac{2}{\mathrm{N}}\rho_{\mathrm{N}-1}\right]$$

where ρ_K is the correlation coefficient expressing the linear dependence of cumulative trading rule returns corresponding to a difference of *k* in the lengths of the longer MA, where *k* is an integer, σ^2 is the population variance and N is the sample size.

Once the standard deviation of m_{G_L} is estimated, then, given the null hypothesis (H_0) that the performance of the trading rule does not differ from the performance of the passive investment strategy (buy and hold), a significance testing can be easily performed following the confidence interval approach: H_0 is accepted if the buy and hold return is within the confidence interval around the mean level of the trading rule cumulative returns. An advantage of this methodology over that usually used is that it can explicitly discriminate among three states: (a) the trading rule performs significantly better than the passive investment strategy; (b) the performance of the rule does differ in a statistically significance sense and it is higher than that of the passive investment strategy; (c) the performance of the trading rule is significantly lower than that of the passive investment strategy. The same methodological steps, as described above for G_L, will also be applied for S_L.

Another issue is to investigate, whether or not, the attenuation (if any) in the performance of the trading rule due to the filtering of the linear interdependencies in index returns is uniform across all lengths of the longer MA. To this end the statistical properties of the series of the differences D_L ($D_L = G_L - S_L$) will be examined.

It is noted that as the trading rule will be applied to two different series (original GEN and simulated index with autocorrelation-free returns), for an application of a particular rule (same length of the longer MA) to the two series, the times τ_j^B, τ_j^S in equations (3) and (4) as well as the frequency of transactions may be quite different. Therefore it makes sense to consider several scenarios. Within the framework stated above such scenarios may be easily simulated. At first the analysis described above will be done both in a costless and a costly environment with a transaction fee of 0.5% per transaction. Further, another scenario is related to the treatment of the investment capital during the periods for which an investor who follows the trading rule signals is out of the market. An obvious choice is to assume that the resulting capital, after a sell order is executed, is invested in a deposit account; hence, the trading rule return would be increased accordingly. So, the significance testing will be performed both with and without explicit consideration of investment in a deposit account. This is also justified due to the considerable variability of interest rates during the period under study, with comparatively higher interest rates for the first two sub-periods and much lower interest rates during the last sub-period. The interest rate of a deposit account will be approximated by the three-month money market interest rate which is readily available (source: World Federation of Exchanges).

4. Results and discussion

Table 1 summarizes some descriptive statistics referring to the returns of the GEN index for the total period and all sub-periods. First it can be noted that returns are non-normal, asymmetric (negatively skewed) and leptokurtic, as is usually the case with index returns (e.g. Mills, 1997; Milionis and Papanagiotou, 2009). Furthermore, the first order autocorrelation coefficient for index returns not only is significant at the 5% level for all time periods, but also has values which can be considered as considerably high as compared to those of similar indices of more developed capital markets (see for instance Brock *et al*. (1992); Mills (1997); Milionis and Papanagiotou (2009)). Hence, substantial linear interdependencies exist in GEN returns. Further, the Ljung-Box statistic (denoted as LBQ), which is a portmanteau statistic for the test of significance of more than one autocorrelation coefficients jointly (Ljung and Box, 1978), was used on the residuals of an AR(1) model of index returns. As is evident, higher than first order autocorrelation, significant at the 5% level, also exists for GEN for the total period, as well as the first and the third sub-periods. Moreover, the value of the first order autocorrelation coefficient for the squares of stock index returns is significant at 5% level for all time periods, and the values of the LBQ statistic are highly significant indicating the existence of higher than first order autocorrelation in the squared stock index returns. Therefore, there is strong evidence of substantial serial correlation in the squares of GEN returns for the total period, as well as for each of the sub-periods indicating nonlinear interdependencies in GEN returns.

As explained in the previous section linear interdependencies in stock index returns can be removed by filtering GEN returns with a linear ARMA filter. Table 2 shows the stochastic models selected for each case following the Box-Jenkins model building approach. The white noise residuals of these models were used to construct the simulated index of autocorrelation-free returns.

It is important to examine, whether or not, there exist nonlinear dependencies in these white noise residuals. In Figures 1 and 2, the plots of the ACF and PACF of the squares of the white noise residuals of GEN returns for the total time period are presented. It is evident that many autocorrelation and partial autocorrelation coefficients are well outside the confidence intervals indicating the presence of strong nonlinear dependencies in GEN returns[3]. Hence, in GEN returns substantial linear, as well as nonlinear interdependencies are present, while in the returns of the simulated index only the nonlinear dependencies exist.

Figure 3 shows the simulated index of autocorrelation-free returns in common plot with the original GEN index. As expected, the new index seems to follow the original GEN index (on their troughs and peaks) in a very consistent way, but on the other hand, the simulated index generates less acute troughs and ridges.

As discussed in the previous section, the MA rule is applied to GEN and to the simulated index for successive values of the length of the longer MA so that the series of successive moving average trading rule cumulative returns are formed. Additionally, we examine whether or not the G_L and S_L series corresponding to each of the various scenarios (with/without transaction cost, with/without investment to a deposit account during the out–of-the-market-periods, total period/sub-periods) are stationary. The most commonly used test for stationarity is the so-called Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979). However, as is well-known (see for instance Hamilton (1994); Enders (1995)), the critical values depend on the presence of any deterministic components. Inevitably, that makes it difficult to perform exploratory analysis, when the researcher does not know the exact specification of the model as the tests for unit roots are conditional on the presence and character of any deterministic regressors and vice versa.

[3] It is noted however, that the confidence intervals are only indicative and should not be taken at face value as stock index returns depart from normality.

In this work, the guidelines suggested by Dolado *et al*. (1990) and Hamilton (1994) will be followed. More specifically, at first the existence of a unit root in the G_L series will be tested in conjunction with a constant and a linear trend ($a_2 L$) in the model:

$$\Delta G_L = \alpha_0 + \gamma G_{L\text{-}1} + \alpha_2 L + \sum \beta_{\mathrm{i}} \Delta G_{L\text{-}\mathrm{i}} + u_L \tag{5}$$

where G_L is the trading rule return for MA length L, α_0, γ, α_2, β_{i} are the model parameters, u_L is the stochastic disturbance and Δ is the difference operator.

After estimation of equation (5), if the hypothesis that $\gamma = 0$ is not rejected and the existence of a time trend is rejected, then (5) is re-estimated without a time trend. If the hypothesis that γ=0 is not rejected but the constant is not found significant, (5) is again re-estimated without a constant. Critical values for the deterministic components at each stage are given by Dickey and Fuller (1979). At any stage if the hypothesis γ=0 is rejected it is concluded that G_L contains no unit root.

To improve the power of the ADF tests (which, as is well known, is low) a modification owing to Elliott *et al*. (1996) the so-called ERS test will also be used.

The critical values are given in Elliott *et al*. (1996). In case the result for unit root testing using ADF and ERS is different the result from ERS will be reported. The same procedure will be followed for the series S_L .

Tables 3 and 4 show the stationarity testing results, based on ADF/ERS tests for the series G_L and S_L for the cases no investment – investment in a deposit account during the out-of-the-market periods, respectively. In addition, for each of the cases where G_L or S_L were stationary, the specification of the corresponding univariate stochastic model is quoted.

As is evident from the results reported in Tables 3 and 4, for both G_L and S_L , two cases (the same ones in both tables) are characterized as unit roots. For these cases the first differences were found to be white noise, thus the G_L and S_L series are random walks and it is apparent that no quantitative conclusions about the predictive power of the trading rule can be made for them. For the rest of the cases, the first remark is that G_L always follows the same type of model for cases corresponding to the same time period and transactions cost in the two tables. The same remark also applies to S_L. Further, in two cases in Table 3 and two cases in Table 4, G_L and S_L are both trend stationary. In two cases the S_L series only is trend stationary, with positive trend slope, while in one case the G_L series only is trend stationary with negative slope. A look at the numerical values of the model parameters in both tables reveals the existence of substantial autocorrelation for G_L and S_L so that on several occasions, although the models are stationary, rather long swings away from the mean level are implied for both G_L and S_L. Nevertheless, for all cases for which G_L and S_L fluctuate around a certain level or trend, significance testing for the predictive performance of the trading rule is possible, as described in the previous section. The results of this significance testing are presented in Tables 5 and 6 for the scenarios with and without inclusion of an additional return in trading rule's cumulative returns due to the investment in a deposit account respectively.

To further facilitate the exposition of the methodology and results, the significance testing procedure is also presented graphically for each scenario and time period in Appendix 2, in which the plots of the G_L and S_L series, together with the corresponding buy and hold return, the mean value of G_L and S_L, and the 95% confidence intervals are shown. For the cases where G_L and S_L are non-stationary, the buy and hold return is drawn, but no quantitative conclusion can be made, as explained earlier. Each case (combination of cost and investment strategy) is classified into one of the following scenarios: Scenario I**:** No transaction costs and no investment to a deposit account; Scenario II: 0.5% fee per transaction and no investment to a deposit account; Scenario III: No transaction costs and an additional return due to investment in a deposit account during out-of-the-market periods; Scenario IV: 0.5% fee per transaction and an additional return due to investment in a deposit account during out-of-the-market periods.

From the results of Tables 5 and 6 and Appendix 2, several interesting comments can be made. It can be noted that our comments will focus mainly on the comparison of the MA trading rules performance as applied to GEN and the simulated index, and not so much on the predictive power of the rule per se, as the latter is discussed in many other works (e.g. Milionis and Papanagiotou, 2009; 2008b). As a first comment from Tables 5 and 6, the comparison at the qualitative level of the MA trading rule performance as applied to G_L and S_L clearly indicates that for any scenario and for all time periods the trading rule performs clearly better when applied to G_L. When there is no such a mean level (i.e. G_L and S_L are non stationary), the same conclusion can be drawn considering fluctuations in cumulative trading rule returns, as reflected in G_L and S_L.

This qualitative argument is formally supported by the results of the statistical inference approach. Indeed, as is apparent from the results of Tables 5 and 6, on several occasions the decision about the acceptance or not of H_0 is altogether different for G_L and S_L. Some striking cases are discussed in more detail below.

Scenario I

For the time period 1993-1997 when the trading rule is applied to the GEN index it outperforms the passive investment strategy, but when it is applied to the simulated index its performance is significantly lower than that of the buy and hold strategy.

Scenario II

For the time period 2001-2005, significance testing for the difference between the mean of the series of trading rule cumulative returns and the buy and hold strategy, as applied to GEN, indicates that there is no difference in the statistical sense. In contrast, when the trading rule is applied to the simulated index its performance is lower than the passive investment strategy.

Scenario III

For the time period 1993-1997, significance testing indicated that the moving average trading rule is clearly more profitable than the passive strategy when applied to GEN, but does not differ statistically from the buy and hold strategy when applied to the simulated index.

Scenario IV

For the time period 2001-2005 when the trading rule is applied to the GEN index its performance does not differ statistically from the performance of the passive investment strategy but is less profitable than the buy and hold strategy, when applied to the simulated index . Moreover, for the periods 1997-2001 and 1993-2005, the trading rule outperforms the market when applied to GEN but when applied to the simulated index outperforms the market from a certain moving average length and beyond.

The above findings indicate that the performance of the trading rule is attenuated when applied to the simulated index of autocorrelation-free residuals. Even for the middle sub-period, during which the speculative bubble occurred, while it is obvious that for most cases the performance of the trading rule is well above the passive investment strategy (Scenario I and Scenario II), for both indices, by looking at the corresponding figures, we can conclude that, on average, the performance of the trading rule as applied to GEN is substantially higher than the performance of the trading rule when the simulated index is considered. Hence, even in a speculative bubble, linear dependencies contribute importantly to the performance of the trading rule.

It is also of much importance to examine whether or not the attenuation in the performance of the trading rule when applied to the simulated index is the same regardless of the length of the longer MA. To this end we considered the series of the differences D_L and we performed the same kind of analysis as for the series G_L and S_L. The results of this analysis are presented in Table 7. The most remarkable comment that can be made regarding these results is that, for the cases where no unit root was present, a trend was present in ten out of thirteen cases. It is very important to note that in all these ten cases the trend was negative! That means that the difference in the performance of the MA trading rule, as applied to the original and the simulated index, is systematically reduced as the length of the longer MA increases. A typical case is shown graphically in Appendix 3. For the real stock index the enhanced performance of the trading rule for the shorter MAs, which is evident in Figure 3, should be attributed to the exploitation of linear dependencies. A possible explanation is that linear dependencies are of markovian type and therefore have a short memory, while non-linear dependencies may be of long memory, as is the case, for instance, with fractal dependence, which is long range and corresponds to biased random walk processes (see for instance Peters (1994)). Such processes are found very often to be present in stock price series (see for instance Cajueiro and Tabak (2004)).

5. Summary and conclusions

The main purpose of this work was to decompose the predictive power of the moving average trading rule and extract the portion that could be attributed to the possible exploitation of linear and non linear dependencies in stock returns. To this end, a new simulated index with autocorrelation-free returns was created by removing any serial dependence from the returns of the General Index of the Athens Stock Exchange. The simulated index moves in phase with the original index through time, but having less acute troughs and ridges. Applying the moving average trading rule to both the original and the simulated indices first, it was found that for both cases cumulative trading rule returns are very sensitive to the choice of the length of the longer moving average and this should be taken into account in future work. Further, using a significance testing approach which takes into consideration this variability in the performance of the trading rule depending on the specific combination of moving average lengths, it was shown that for all the scenarios considered, the predictive power of the MA trading rule is clearly reduced once linear dependencies in the returns of the stock index are removed. That implies that a substantial part of the performance of the MA trading rule can be attributed to the exploitation of linear dependencies in stock returns. To some extent, this conclusion contradicts the prevailing belief that the predictive power of the trading rules of technical analysis is to be attributed mainly to the existence of nonlinearities in stock returns (e.g. Neftci, 1991; Brock *et al.*, 1992). Finally, it was found that the attenuation of the trading rule's performance after filtering out linear dependencies in stock returns is not the same for all the lengths of the longer moving average. Indeed there exists a systematic decrease in the differential performance of the trading rule as the length of the longer MA increases. That means that the contribution of linear dependencies is maximized at the shorter moving averages. We attributed these empirical finding to the fact that linear dependencies are short memory, while nonlinear dependencies, such as fractal dependence, are long memory processes. Of course further research is needed to substantiate this allegation more solidly.

References

Alexakis P. and Xanthakis M. (1995) 'Day of the Week Effect on the Greek Stock Market', *Applied Financial Economics*, 5, pp. 43-50.

Bessembinder H. and Chan K. (1995) 'The Profitability of Technical Trading Rules in the Asian Stock Markets', *Pacific-Basin Finance Journal*, 3, pp. 257-84.

Bessembinder H. and Chan K. (1998) 'Market Efficiency and the Returns to Technical Analysis', *Financial Management*, 27, pp. 5-17.

Box G. E. P. and Jenkins G. M. (1976) *Time Series Analysis: Forecasting and Control*, revised edition, Holden Day, San Francisco.

Brock W., Lakonishok J. and LeBaron B. (1992) 'Simple Technical Trading Rules and the Stochastic Properties of Stock Returns', *Journal of Finance*, XLVII(5), pp. 1731-1764.

Cai B. M., Cai C. X. and Keasey K. (2005) 'Market Efficiency and Returns to Simple Technical Trading Rules: Further Evidence from U.S., U.K., Asian and Chinese Stock Markets', *Asia-Pacific Financial Markets*, 12, pp. 45-60.

Cajueiro D. O. and Tabak B. M. (2004) 'Ranking Efficiency for Emerging Markets', *Chaos Solitons &Fractals*, 22, pp. 349-52.

Dickey S. A. and Fuller W. A. (1979) 'Distribution of the Estimators for Autoregressive Time Series with a Unit Root', *Journal of the American Statistical Association*, 74, pp. 427-31.

Dolado J., Jenkinson T. and Sosvilla-Rivero S. (1990) 'Cointegration and Unit Roots', *Journal of Economic Surveys*, 4, pp. 249-73.

Elliott G., Rothenberg T. J. and Stock J. H. (1996) "Efficient Tests for an Autoregressive Unit Root", *Econometrica*, 64, pp. 813-36.

Enders W. (1995) *Applied Econometric Time Series*, John Wiley, New York.

Fama E. (1970) 'Efficient Capital Markets: A Review of Theory and Empirical Work', *Journal of Finance*, XV (2), pp. 383-417.

Fama E. (1991) 'Efficient Capital Markets II', *Journal of Finance*, 26 (5), pp. 1557-1617.

Fang Y. and Xu D. (2003) 'The Predictability of Asset Returns: An Approach Combining Technical Analysis and Time Series Forecasts', *International Journal of Forecasting*, 19, pp. 369-85.

Fernandez-Rodriguez F., Sosvilla-Rivero S. and Andrada-Felix J. (2003) 'Technical Analysis in Foreign Exchange Markets: Evidence from the EMS', *Applied Financial Economics,* 13, pp. 113-22.

Goldberger A. S. (1991) *A Course in Econometrics*, Harvard University Press, Cambridge, MA.

Hamilton J. (1994) *Time Series Analysis*, Princeton University Press, Princeton, NJ.

Hundson R., Dempsey M. and Keasy K. (1996) 'A Note on the Weak Form Efficiency of Capital Markets: The Application of Simple Technical Trading Rules to UK Stock Prices – 1935 to 1994', *Journal of Banking and Finance*, 20, pp. 1121-1132.

Kavussanos M. G. and Dockery E.(2001) 'A Multivariate Test for Stock Market Efficiency: The Case of ASE', *Applied Financial Economics*, 11(5), pp. 573-79.

Kwon K. Y. and Kish R.J. (2002) 'Technical Trading Strategies and Return Predictability: NYSE', *Applied Financial Economics*, 12, pp. 639-53.

G. M. Ljung – G.E.P. Box (1978) 'On a Measure of Lack of Fit in Time Series Models', *BiometriKa*, 65, pp. 297-303.

Milionis A. E and Papanagiotou E. (2008a) 'A Note On the Use of Moving Average Trading Rule to Test for Weak Form Efficiency in Capital Markets'. Working Paper 91, Bank of Greece.

Milionis A. E. and Papanagiotou E. (2008b) 'On the Use of the Moving Average Trading Rule to Test for Weak Form Efficiency in Capital Markets', *Economic Notes, Review of Banking, Finance and Monetary Economics*, 37, pp. 181-201.

Milionis A. E. and Papanagiotou E. (2009) 'A study of predictive performance of the moving average trading rule as applied to NYSE, the Athens Stock Exchange, and the Vienna Stock Exchange: sensitivity analysis and implications for weak form market efficiency testing.', *Applied Financial Economics*, 19, pp. 1171-1186.

Mills T. (1997) 'Technical Analysis and the London Stock Exchange: Testing Trading Rules Using the FT30', *International Journal of Finance & Economics*, 2, pp. 319-31.

Murphy J. J. (1986) *Analysis of the Future Markets: A Comprehensive Guide to Trading Methods and Applications*, New York Institute of Finance, Prentice Hall, New York.

Neftci S. N. (1991) 'Naive Trading Rules in Financial Markets and Wiener-Kolmogorov Prediction Theory: A Study of Technical Analysis', *Journal of Business*, 64 (4), pp. 549-71.

Olson D. (2004) 'Have Trading Rule Profits in the Currency Markets Declined Over Time?', *Journal of Banking and Finance*, 28(1), pp. 85-105.

Panagiotidis T. (2009) 'Market Efficiency and the Euro: The Case of the Athens Stock Exchange', *Empirica*, DOI: 10.1007/s10663-008-9100-5.

Peters E. E. (1994) *Fractal Market Analysis: Applying Chaos Theory to Investment and Economics*, John Wiley & Sons, New York.

Pring M. J. (1991) *Technical Analysis Explained*, 3rd edition, McGraw-Hill, New York.

Appendix 1

Augmented Sample Mean Theorem

Let X_1, X_2, ..., X_N be a series of linearly interdependent random variables, representing a non random sample of size N from a population with mean μ and variance σ^2. If ρ_k k=1,2,... represents the autocorrelation function of that series then:

(a) The sample mean $\bar{X}$ is an unbiased estimator of μ

(b) The variance of the sample mean is given by:

$$VAR(\bar{X}) = \frac{\sigma^2}{\mathrm{N}}\left[1 + \frac{2(\mathrm{N}-1)}{\mathrm{N}}\rho_1 + \frac{2(\mathrm{N}-2)}{\mathrm{N}}\rho_2 + \ldots + \frac{2}{\mathrm{N}}\rho_{\mathrm{N}-1}\right]$$

Proof:

The expected value of the sample mean $\bar{X}$ will be

$$\mathrm{E}(\bar{X}) = \frac{1}{\mathrm{N}}\mathrm{E}(\mathrm{X}_1 + \mathrm{X}_2 + \ldots + \mathrm{X}_\mathrm{N}) = \frac{1}{\mathrm{N}}\mathrm{N}\mu = \mu \qquad \text{Q.E.D.}$$

The variance of $\bar{X}$ will be

$$VAR(\bar{X}) = \frac{1}{\mathrm{N}^2}VAR\left[\mathrm{X}_1 + \mathrm{X}_2 + \ldots \mathrm{X}_\mathrm{N} + \sum_{i=1}^{\mathrm{N}}\sum_{\substack{j=1\\ i\neq j}}^{\mathrm{N}}\mathrm{cov}(\mathrm{X}_i, \mathrm{X}_j)\right] \qquad (1A)$$

But $\mathrm{cov}(\mathrm{X}_i, \mathrm{X}_j) = \rho_{|i-j|}\sigma^2$ (2A)

Overall there will be ${}_{\mathrm{N}}\mathrm{P}_2 = \frac{\mathrm{N}!}{(\mathrm{N}-2)!} = (\mathrm{N}-1)\mathrm{N}$ autocovariances, of which $2(\mathrm{N}-1)$ will be of first order (as $\mathrm{cov}(\mathrm{X}_j, \mathrm{X}_{j+1}) = \mathrm{cov}(\mathrm{X}_j, \mathrm{X}_{j-1})$), $2(\mathrm{N}-2)$ will be of second order, etc, and 2 will be of order $\mathrm{N}-1$. Hence, from (1A) and (2A) we have:

$$VAR(\bar{X}) = \frac{1}{\mathrm{N}^2}\left[\mathrm{N}\sigma^2 + 2(\mathrm{N}-1)\rho_1\sigma^2 + 2(\mathrm{N}-2)\rho_2\sigma^2 + \ldots + 2\sigma^2\rho_{\mathrm{N}-1}\right] =$$

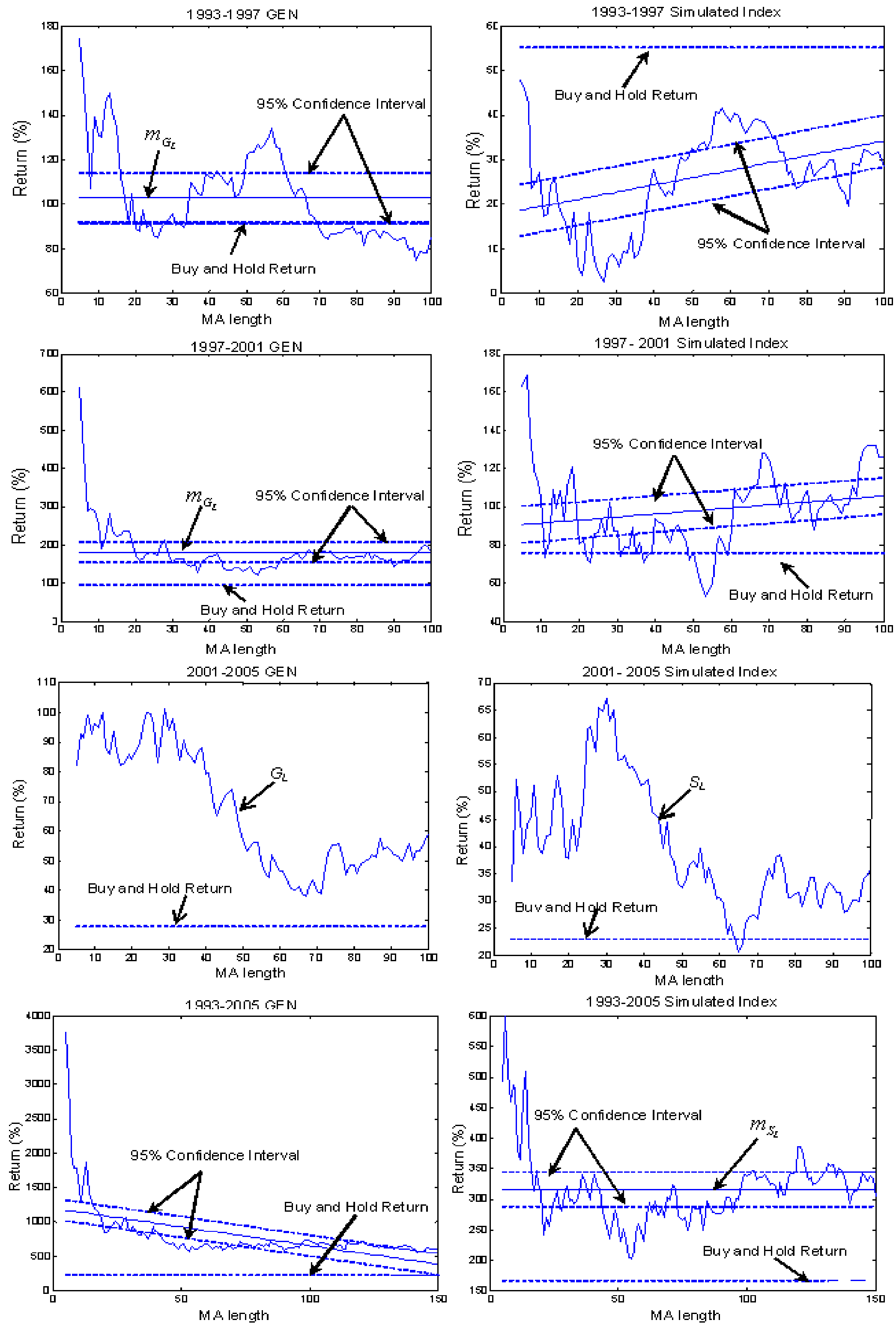
$$= \frac{\sigma^2}{\mathrm{N}}\left[1 + 2\frac{(\mathrm{N}-1)}{\mathrm{N}}\rho_1 + 2\frac{(\mathrm{N}-2)}{\mathrm{N}}\rho_2 + \ldots + \frac{2}{\mathrm{N}}\rho_{\mathrm{N}-1}\right]$$

Q.E.D.

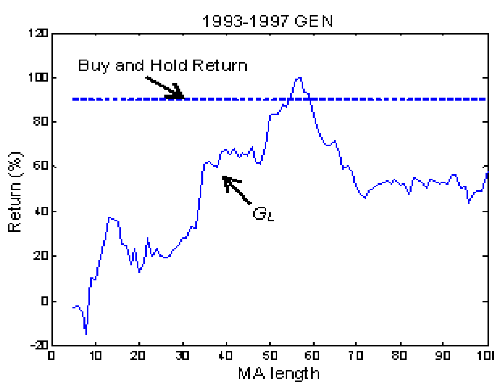
Appendix 2

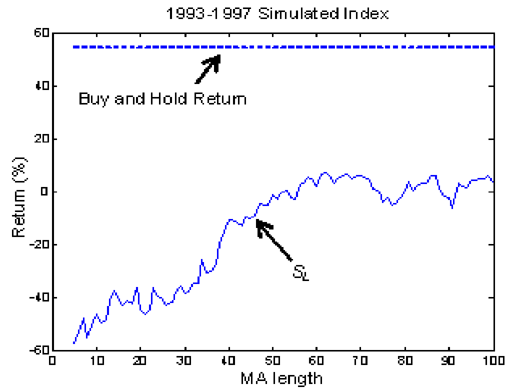
Graphical representation of the significance testing procedure. Each figure shows the G_L or S_L series. Dash lines represent the total return from the buy and hold strategy and the estimated confidence interval on both sides of the mean level around which G_L or S_L fluctuate.

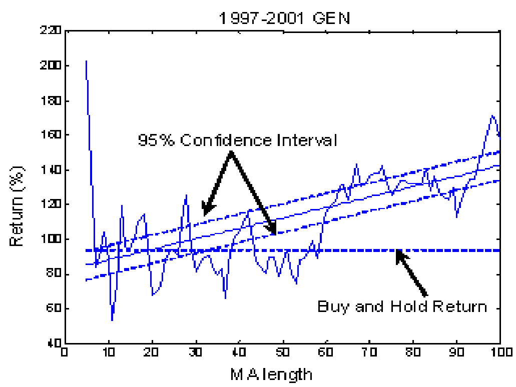
Scenario I: No transaction costs and no additional return due to investment in a deposit account during the out-of-the-market periods are included in trading rule cumulative returns.

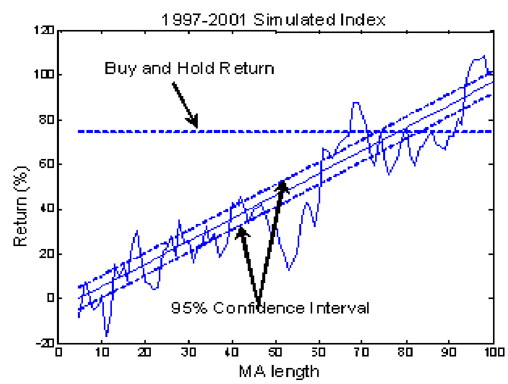


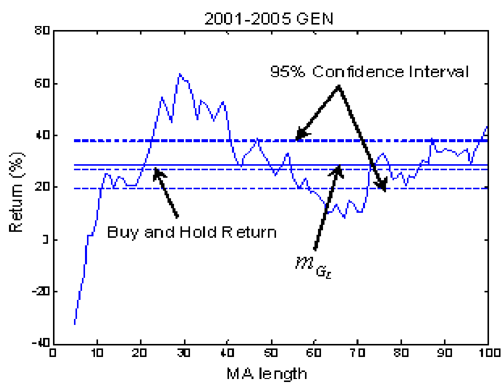
Scenario II: 0.5% fee per transaction and no additional return due to investment in a deposit account during the out-of-the-market periods are included in trading rule cumulative returns.

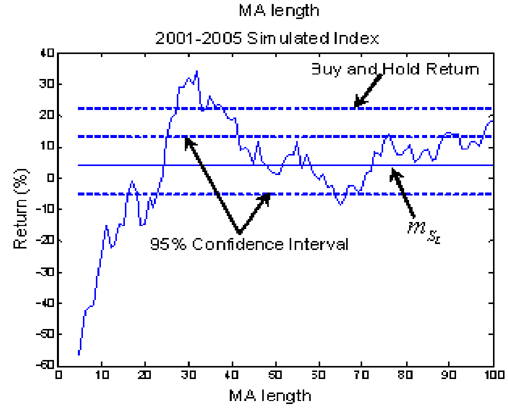


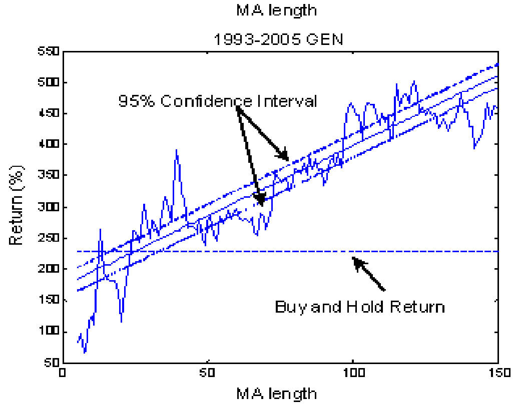


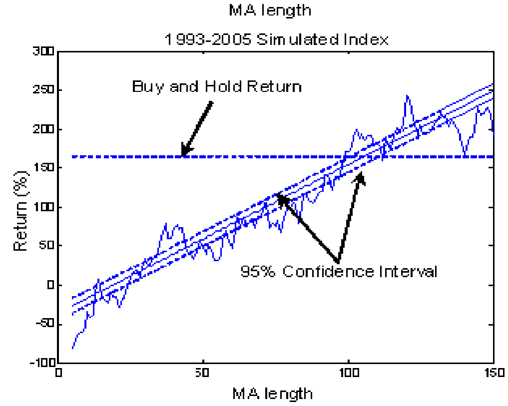




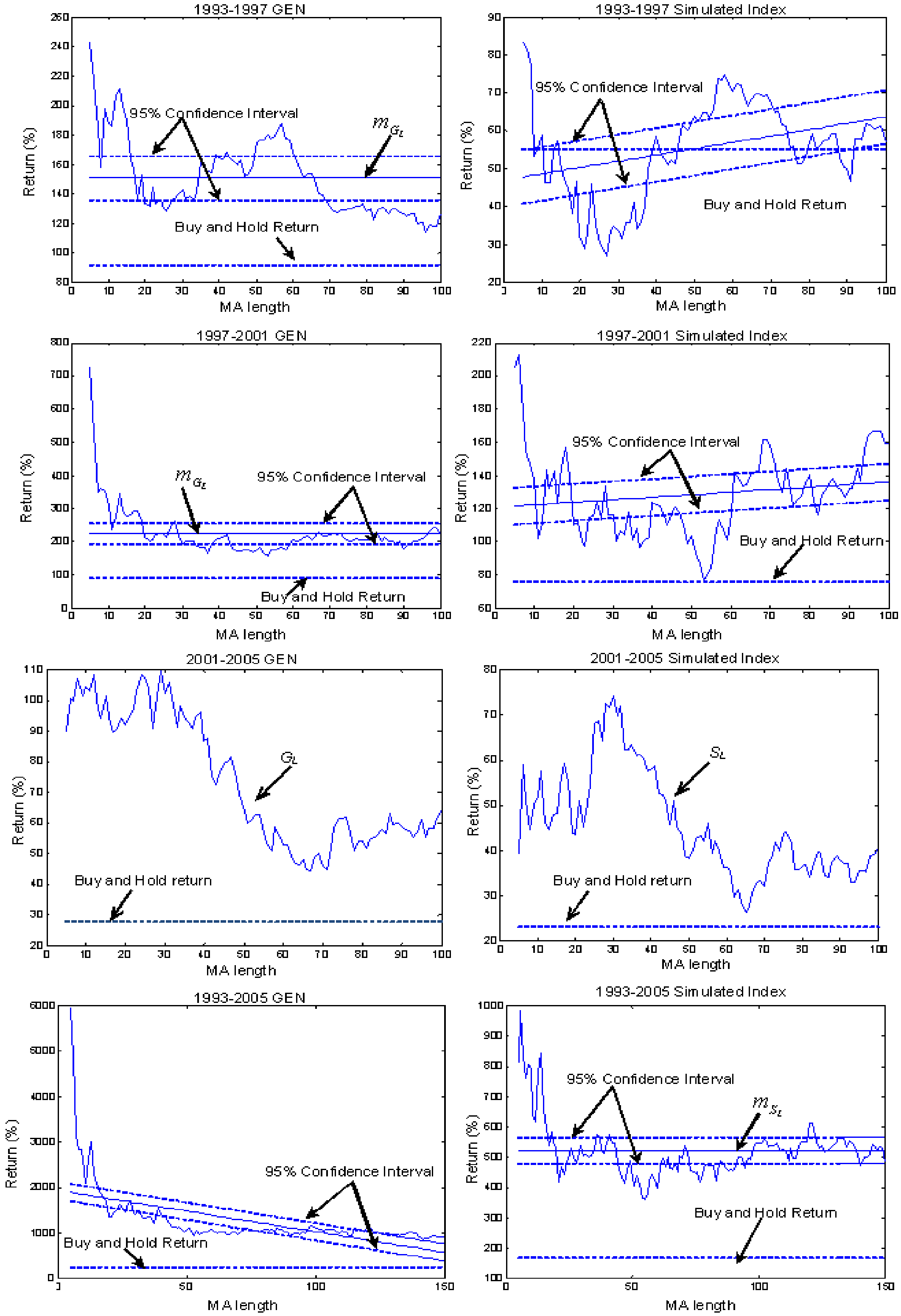




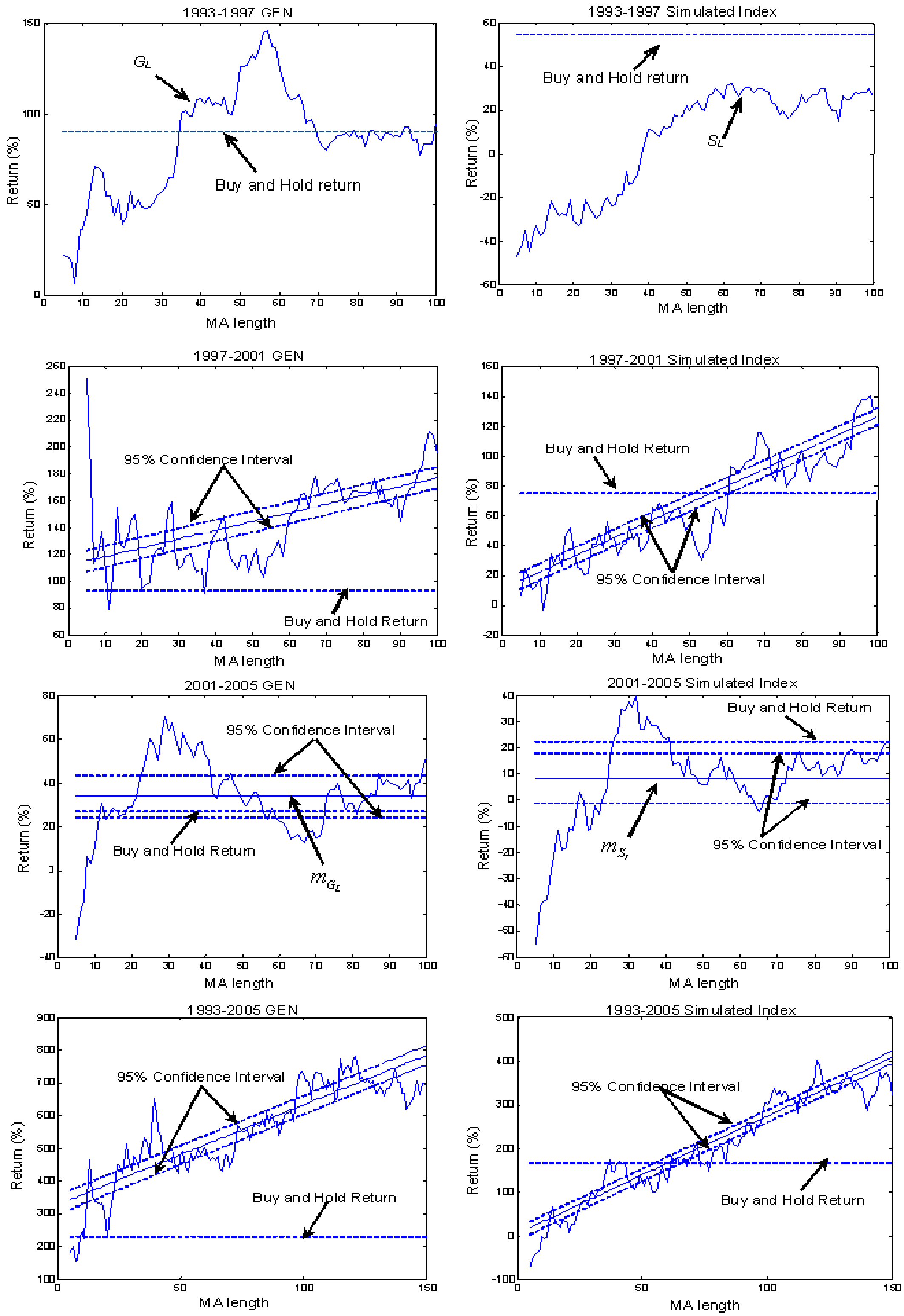




Scenario III: No transaction costs and an additional return due to investment in a deposit account during the out-of-the-market periods are included in trading rule cumulative returns.



Scenario IV: 0.5% fee per transaction and an additional return due to investment in a deposit account during the out-of-the-market periods are included in trading rule cumulative returns.



Appendix 3

Performance of the MA trading rule when applied to the original and the simulated indices and their difference as a function of the length of MA (case with time period 1993-2005, no transaction cost, no additional return due to investment in a deposit account during the out-of-the-market periods are included in trading rule cumulative returns).

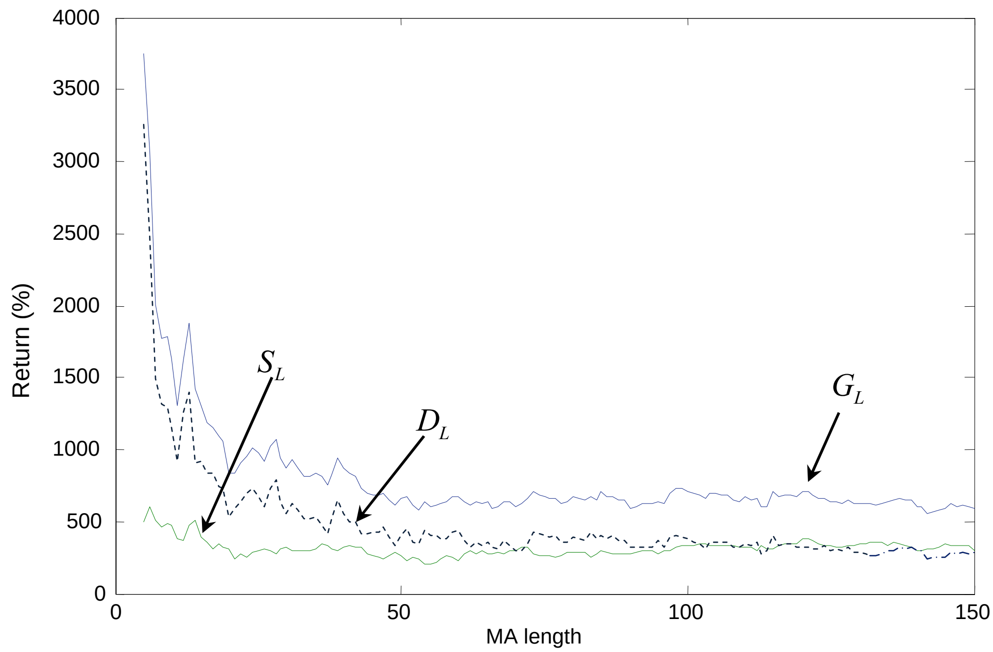


Figure 1: Plot of the sample autocorrelation function of the series of squared white noise residuals of stock index returns for the total time period (1993-2005). Crosses represent the 95% confidence interval.

```
         -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                             I
 1   0.095                  + IXX
 2   0.330                  + IX+XXXXXX
 3   0.120                  + IX+X
 4   0.150                  + IX+XX
 5   0.130                  + IX+X
 6   0.157                  + IX+XX
 7   0.046                  + IX+
 8   0.112                  + IX+X
 9   0.007                  + I +
 10   0.038                  + IX+
 11   0.041                  + IX+
 12   0.062                  + IXX
```

Figure 2: Plot of the sample partial autocorrelation function of the series of squared white noise residuals of stock index returns. Crosses represent the 95% confidence interval.

```
         -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
LAG   CORR. +----+----+----+----+----+----+----+----+----+----+
                             I
 1   0.095                  + IXX
 2   0.324                  + IX+XXXXXX
 3   0.077                  + IXX
 4   0.037                  + IX+
 5   0.068                  + IXX
 6   0.095                  + IXX
 7  -0.041                  +XI +
 8   0.021                  + IX+
 9  -0.034                  +XI +
 10  -0.027                  +XI +
 11   0.025                  + IX+
 12   0.047                  + IX+
```

Figure 3: Common plots for the GEN index and the simulated index of autocorrelation-free returns.

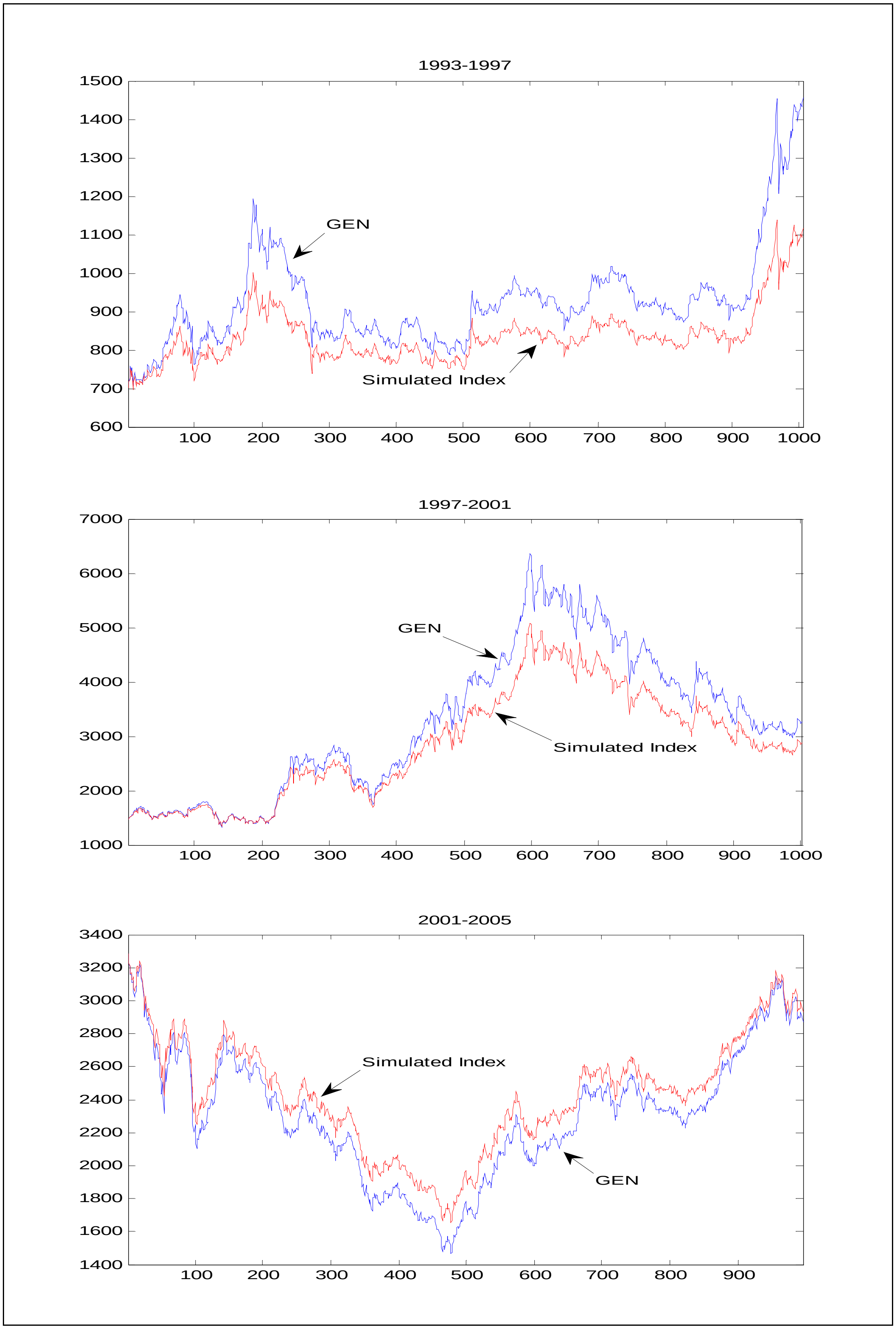


Table 1: Summary statistics for daily stock index returns.

	1993-1997	**1997-2001**	**2001-2005**	**1993-2005**
mean*10^{-4}	7.7155 (*)	7.9982	-1.3674	4.6486
std	0.013	0.021	0.012	0.016
skewness	-0.271	-0.018	-0.320	-0.083
kurtosis	4.861	1.721	3.281	3.755
KS- test	0.478 (**)	0.466 (**)	0.481 (**)	0.472 (**)
ρ(1)	0.176 (**)	0.173 (**)	0.088 (**)	0.158 (**)
LBQ(10) (in res. of AR(1) model)	39.65 (**)	2.27	18.26 (**)	58.88 (**)
ρ^2(1)	0.320 (**)	0.190 (**)	0.090 (**)	0.244 (**)
LBQ(10) (in res. of AR(1) model)	104.59 (**)	68.49 (**)	190.42 (**)	269.34 (**)

One asterisk (*) indicates significance at 10% level. Two asterisks (**) indicate significance at 5% level .The Kolmogorov-Smirnov (KS-test) critical value is 0.042 (sub periods) 0.024 (full period). X_9^2 critical values (for LBQ-statistic): 14.68 (10%), 16.91(5%).

Table 2: Stochastic models for GEN returns selected using the Box-Jenkins model building approach.

Time Period	**Model**
1993-1997	$R_t = 0.22\varepsilon_{t-1} + 0.11\varepsilon_{t-6} + 0.06\varepsilon_{t-7} + 0.12\varepsilon_{t-8} - 0.05\varepsilon_{t-10} + 0.13\varepsilon_{t-11} + \varepsilon_t$
1997-2001	$R_t = 0.18\varepsilon_{t-1} + \varepsilon_t$
2001-2005	$R_t = 0.07\varepsilon_{t-1} + 0.10\varepsilon_{t-4} + \varepsilon_t$
1993-2005	$R_t = 0.16\varepsilon_{t-1} - 0.05\varepsilon_{t-12} + \varepsilon_t$

Table 3: Results on stationarity testing for G_L, S_L and model specification for the stationary cases. No additional return due to investment in a deposit account during the out-of-the-market periods is included in trading rule cumulative returns.

Time Period	**Trans. Cost**	G_L		S_L	
		Result of Stationarity Test	**Model Specification**	**Result of Stationarity Test**	**Model Specification**
1993-1997	0	stationary series	$G_L = 14.85 + 0.90G_{L-1} + \varepsilon_L$	trend stationary series	$S_L = 17.69 + 0.16L + 0.86G_{L-1} + \varepsilon_L$
	0.5	unit root	$G_L = G_{L-1} + \varepsilon_L$	unit root	$S_L = S_{L-1} + \varepsilon_L$
1997-2001	0	stationary series	$G_L = 37.95 + 0.85G_{L-1} - 0.34G_{L-2} + 0.26G_{L-3} + \varepsilon_L$	trend stationary series	$S_L = 89.90 + 0.15L + 0.81G_{L-1} + \varepsilon_L$
	0.5	trend stationary series	$G_L = 82.20 + 0.59L + 0.86G_{L-1} - 0.38G_{L-2} + 0.27G_{L-3} + \varepsilon_L$	trend stationary series	$S_L = -4.96 + 1.01L + 0.75S_{L-1} + \varepsilon_L$
2001-2005	0	unit root	$G_L = G_{L-1} + \varepsilon_L$	unit root	$S_L = S_{L-1} + \varepsilon_L$
	0.5	stationary series	$G_L = 3.42 + 1.11G_{L-1} - 0.21G_{L-2} + \varepsilon_L$	stationary series	$S_L = 1.22 + 0.88S_{L-1} + \varepsilon_L$
1993-2005	0	trend stationary series	$G_L = 1194.75 - 5.40L + 0.87G_{L-1} - 0.33G_{L-2} + 0.43G_{L-3} - 0.04G_{L-4} + \varepsilon_L$	stationary series	$S_L = 42.11 + 0.92S_{L-1} - 0.35S_{L-2} + 0.29S_{L-3} + \varepsilon_L$
	0.5	trend stationary series	$G_L = 173.10 + 2.25L + 0.82G_{L-1} + \varepsilon_L$	trend stationary series	$S_L = -35.80 + 1.89L + 0.84S_{L-1} + \varepsilon_L$

Table 4: Results on stationarity testing for G_L, S_L and model specification for the stationary cases. An additional return due to investment in a deposit account during the out-of-the-market periods is included in trading rule cumulative returns.

Time Period	**Trans. Cost**	G_L		S_L	
		Result of Stationatity Test	**Model Specification**	**Result of Stationatity Test**	**Model Specification**
1993-1997	0	stationary series	$G_L = 19.85 + 0.86G_{L-1} + \varepsilon_L$	trend stationary series	$S_L = 46.92 + 0.16L + 0.86G_{L-1} + \varepsilon_L$
	0.5	unit root	$G_L = G_{L-1} + \varepsilon_L$	unit root	$S_L = S_{L-1} + \varepsilon_L$
1997-2001	0	stationary series	$G_L = 45.87 + 0.86G_{L-1} - 0.34G_{L-2} + 0.26G_{L-3} + \varepsilon_L$	trend stationary series	$S_L = 120.66 + 0.15L + 0.81G_{L-1} + \varepsilon_L$
	0.5	trend stationary series	$G_L = 111.78 + 0.65L + 0.88G_{L-1} - 0.37G_{L-2} + 0.25G_{L-3} + \varepsilon_L$	trend stationary series	$S_L = 10.53 + 1.15L + 0.74S_{L-1} + \varepsilon_L$
2001-2005	0	unit root	$G_L = G_{L-1} + \varepsilon_L$	unit root	$S_L = S_{L-1} + \varepsilon_L$
	0.5	stationary series	$G_L = 4.97 + 0.88G_{L-1} + \varepsilon_L$	stationary series	$S_L = 1.73 + 0.88S_{L-1} + \varepsilon_L$
1993-2005	0	trend stationary series	$G_L = 1929.47 - 9.07L + 0.99G_{L-1} - 0.34G_{L-2} + 0.45G_{L-3} - 0.18G_{L-4} + \varepsilon_L$	stationary series	$S_L = 72.14 + 0.91S_{L-1} - 0.35S_{L-2} + 0.29S_{L-3} + \varepsilon_L$
	0.5	trend stationary series	$G_L = 328.72 + 3.04L + 0.83G_{L-1} + \varepsilon_L$	trend stationary series	$S_L = 4.26 + 2.68L + 0.84S_{L-1} + \varepsilon_L$

Table 5: Results of the significance testing for the difference between mean trading rule cumulative return (m_{G_L}, m_{S_L}) and buy and hold total return (BH).

s_m represents the standard deviation from the mean and $|s_m * 1.96|$ is the absolute value of the 95% confidence interval around the mean**.** No additional return due to investment in a deposit account during the out-of-the-market periods is included in trading rule cumulative returns.

INDEX	Time Period	Trans. Cost	m_{G_L}	$\|s_m * 1.96\|$	BH	H₀
GEN	1993-1997	0	102.81	11.08	91.19	rejected in favour of BH<TR
	1997-2001	0	181.70	26.77	94.25	rejected in favour of BH<TR
		0.5	-	-	93.28	rejected for lag>32 in favour of BH<TR
	2001-2005	0.5	28.60	9.00	26.99	accepted
	1993-2005	0	-	-	231.38	rejected in favour of BH<TR
		0.5	-	-	229.72	rejected for lag>33 in favour of BH<TR
	Time Period	**Trans. Cost**	m_{S_L}	$\|s_m * 1.96\|$	**BH**	**H_0**
Simulated Index	1993-1997	0	-	-	55.19	rejected in favour of TR<BH
	1997-2001	0	-	-	75.63	rejected in favour of BH<TR
		0.5	-	-	74.75	rejected for lag>83 in favour of BH<TR
	2001-2005	0.5	4.06	9.10	22.43	rejected in favour of TR<BH
	1993-2005	0	315.72	28.59	166.79	rejected in favour of BH<TR
		0.5	-	-	165.46	rejected for lag>110 in favour of BH<TR

Table 6: Results of the significance testing for the difference between mean trading rule cumulative return (m_{G_L} , m_{S_L}) and buy and hold total return (BH).

s_m represents the standard deviation from the mean and | s_m *1.96| is the absolute value of the 95% confidence interval around the mean**.** An additional return due to investment in a deposit account during the out-of-the-market periods is included in trading rule cumulative returns.

INDEX	**Time Period**	**Trans. Cost**	m_{G_L}	$\|s_m *1.96\|$	**BH**	**H_0**
GEN	1993-1997	0	150.59	15.18	91.19	rejected in favour of BH<TR
	1997-2001	0	224.97	31.51	94.25	rejected in favour of BH<TR
		0.5	-	-	93.28	rejected in favour of BH<TR
	2001-2005	0.5	33.72	9.63	26.99	accepted
	1993-2005	0	-	-	231.38	rejected in favour of BH<TR
		0.5	-	-	229.72	rejected in favour of BH<TR
	Time Period	**Trans. Cost**	m_{S_L}	$\|s_m *1.96\|$	**BH**	**H_0**
Simulated Index	1993-1997	0	-	-	55.19	rejected for lag>92 in favour of BH<TR
	1997-2001	0	-	-	75.63	rejected in favour of BH<TR
		0.5	-	-	74.75	rejected for lag>60 in favour of BH<TR
	2001-2005	0.5	8.40	9.46	22.43	rejected in favour of TR<BH
	1993-2005	0	521.16	43.92	166.79	rejected in favour of BH<TR
		0.5	-	-	165.46	rejected for lag>65 in favour of BH<TR

Table 7: Results from stationarity testing for the series $D_L = G_L - S_L$ and model specification for the stationary cases.

	Time Period	Trans. Cost	Result of Stationarity Testing	Model Specification
No rate	1993-1997	0	trend stationary	$D_L = 106.11 - 0.59L + 0.72D_{L-1} + e_L$
		0.5	unit root	-
	1997-2001	0	trend stationary	$D_L = 138.77 - 1.12L + 0.68D_{L-1} + 0.09D_{L-4} + e_L$
		0.5	trend stationary	$D_L = 87.16 - 0.41L + 0.49D_{L-1} + 0.16D_{L-4} + e_L$
	2001-2005	0	unit root	-
		0.5	trend stationary	$D_L = 33.72 - 0.18L + 0.62D_{L-1} + e_L$
	1993-2005	0	trend stationary	$D_L = 871.26 - 5.26L + 0.82D_{L-1} - 0.17D_{L-2} + 0.38D_{L-3} - 0.14D_{L-4} + e_L$
		0.5	stationary	$D_L = 77.83 + 0.67D_{L-1} + e_L$
Rate	1993-1997	0	trend stationary	$D_L = 131.50 - 0.73L + 0.71D_{L-1} + e_L$
		0.5	unit root	-
	1997-2001	0	trend stationary	$D_L = 165.36 - 1.31L + 0.69D_{L-1} + 0.08D_{L-4} + e_L$
		0.5	trend stationary	$D_L = 103.45 - 0.47L + 0.50D_{L-1} + 0.16D_{L-4} + e_L$
	2001-2005	0	stationary	$D_L = 3.33 + 0.87D_{L-1} + e_L$
		0.5	trend stationary	$D_L = 34.78 - 0.17L + 0.60D_{L-1} + e_L$
	1993-2005	0	trend stationary	$D_L = 1372.67 - 8.58L + 0.72D_{L-1} - 0.28D_{L-2} - 0.1D_{L-3} + e_L$
		0.5	stationary	$D_L = 126.54 + 0.64D_{L-1} + e_L$

BANK OF GREECE WORKING PAPERS

116. Tagkalakis, A., “Fiscal Policy and Financial Market Movements”, July 2010.
117. Brissimis, N. S., G. Hondroyiannis, C. Papazoglou, N. T Tsaveas and M. A. Vasardani, “Current Account Determinants and External Sustainability in Periods of Structural Change”, September 2010.
118. Louzis P. D., A. T. Vouldis, and V. L. Metaxas, “Macroeconomic and Bank-Specific Determinants of Non-Performing Loans in Greece: a Comparative Study of Mortgage, Business and Consumer Loan Portfolios”, September 2010.
119. Angelopoulos, K., G. Economides, and A. Philippopoulos, “What Is The Best Environmental Policy? Taxes, Permits and Rules Under Economic and Environmental Uncertainty”, October 2010.
120. Angelopoulos, K., S. Dimeli, A. Philippopoulos, and V. Vassilatos, “Rent-Seeking Competition From State Coffers In Greece: a Calibrated DSGE Model”, November 2010.
121. Du Caju, P.,G. Kátay, A. Lamo, D. Nicolitsas, and S. Poelhekke, “Inter-Industry Wage Differentials in EU Countries: What Do Cross-Country Time Varying Data Add to the Picture?”, December 2010.
122. Dellas H. and G. S. Tavlas, “The Fatal Flaw: The Revived Bretton-Woods system, Liquidity Creation, and Commodity-Price Bubbles”, January 2011.
123. Christopoulou R., and T. Kosma, “Skills and wage Inequality in Greece: Evidence from Matched Employer-Employee Data, 1995-2002”, February 2011.
124. Gibson, D. H., S. G. Hall, and G. S. Tavlas, “The Greek Financial Crisis: Growing Imbalances and Sovereign Spreads”, March 2011.
125. Louri, H. and G. Fotopoulos, “On the Geography of International Banking: the Role of Third-Country Effects”, March 2011.
126. Michaelides, P. G., A. T. Vouldis, E. G. Tsionas, “Returns to Scale, Productivity and Efficiency in Us Banking (1989-2000): The Neural Distance Function Revisited”, March 2011.
127. Gazopoulou, E. “Assessing the Impact of Terrorism on Travel Activity in Greece”, April 2011.
128. Athanasoglou, P. “The Role of Product Variety and Quality and of Domestic Supply in Foreign Trade”, April 2011.
129. Galuščǻk, K., M. Keeney, D. Nicolitsas, F. Smets, P. Strzelecki and Matija Vodopivec, “The Determination of Wages of Newly Hired Employees: Survey Evidence on Internal Versus External Factors”, April 2011.
130. Kazanas, T., and. E. Tzavalis, “Unveiling the Monetary Policy Rule In Euro-Area”, May 2011.
131. Milionis, A. E., and D. Patsouri, “A Conditional CAPM; Implications for the Estimation of Systematic Risk”, May 2011

132. Christodoulakis, N., and V. Sarantides, "External Asymmetries in the Euro Area and The Role Of Foreign Direct Investment", June 2011.

133. Tagkalakis, A., "Asset Price Volatility and Government Revenue", June 2011.