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AN ALTERNATIVE METHODOLOGICAL APPROACH TO ASSESS THE PREDICTIVE PERFORMANCE OF THE MOVING AVERAGE TRADING RULE IN FINANCIAL MARKETS: APPLICATION TO THE LONDON STOCK EXCHANGE.

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ABSTRACT

In this work a modification of the Box-Tiao methodology for the assessment of the impact of external events on time series is proposed as an alternative statistical approach of assessing the predictive performance of the moving average trading rule in financial markets. With the proposed methodology measures of the predictive performance of the moving average trading rule can be simultaneously estimated, while at the same time controlling for autocorrelation in the series of asset returns. The potential advantages of the proposed methodology over the existing ones are discussed. Application of this alternative methodology to the returns of the FT30 Index of the London Stock Exchange shows good agreement with the empirical findings of other methods.

Keywords: Market Efficiency, Trading Rules, Moving Averages, Impact Assessment, Box-Tiao Models, London Stock Exchange.
JEL classification: G14, G17, C32

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1. Introduction

The concept of market efficiency is very important in modern financial theory. Although market efficiency is defined differently by different authors (e.g. Rubinstein 1975; Beaver 1981; Malkiel 1992; Milionis 2007), it is the definition due to Fama (1970) that has become the established one, according to which a market is efficient if "*prices "fully reflect" all available information*". The classic categorization of available information, introduced by Roberts (1959) and adopted by Fama (1970), classifies efficiency as weak-form, when the information set includes past prices, semi-strong, when the information set includes all publicly available information, and strong-form, when the information set includes all publicly or privately available information. In the so-called tests for return predictability (Fama 1991), the information set available, in addition to past prices (which is the information set in the tests for weak-form market efficiency) may also include firm-specific characteristics (e.g. the firm size, the price-earnings ratio, the book-to-market value and the dividend yield), macroeconomic variables (e.g. variables related to the term structure of interest rates and unexpected inflation) or even calendar effects (Fama 1991). In an efficient market the results from tests of return predictability should not reject the null hypothesis of no predictability. On the other hand, the so-called technical analysis (i.e. the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends (Murphy 1986)) has been a thriving activity for more than a century. Although until late 1980s most empirical testing was suggestive of non-rejection of the efficiency hypothesis in its weak and semi-strong versions, during the 1990s there was an abundance of counter-evidence, mainly from examining the use of trading rules suggested by technical analysis. The spark that ignited this new discussion on the subject of market efficiency was the work of Brock et al. (1992). Indeed, Brock et al. (1992), using daily data of the Dow Jones Index of the New York Stock Exchange for nearly a century, showed that many trading rules have predictive power. This conclusion was then generalized for both developed and emerging capital markets (see for example Hudson et al. 1996; Bessembinder and Chan 1995; Gençay 1996; Wong et al. 2003; Cai et al. 2005).

Among the trading rules used by researchers to test market efficiency the one employed most frequently is the so-called moving average (henceforth MA) rule. In contrast to other rules of technical analysis, the MA trading rule is mathematically well defined (Neftci 1991) and is used by most market analysts (Taylor and Allen 1992). It is noted that, although technical analysis stresses that a buy or a sell decision is best to be a composite one, being based on as many conducive signals as possible (e.g. volume of trade, convergence-divergence indicators, etc. (Murphy 1986)), quite often the MA rule, due to the precise signals it generates, is used as a stand-alone method, particularly in the automated trend-following trading systems. In that way, it becomes a purely "mechanical", rather than technical, trading rule. Even in its "mechanical" use, however, the MA trading rule may have several versions (see for instance Pring 1991). In one of its simplest versions, two non- centred, moving averages with different length are created from the time series of stock prices:

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

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

where MAL_t represents the relatively longer MA with length N, calculated at time t, MAS_t represents the relatively shorter MA with length M, P_t is the stock price at time t, θ_i are non-time varying parameters, and B is the backward shift operator, i.e. $\mathrm{B}^i P_{t-i}$. Buy (sell) signals are then generated when the relatively shorter moving average penetrates the longer moving average from below (above).

A usual way of measuring the predictive power of the trading rule is to test for the statistical significance of the difference between: the mean return of individual trading periods characterized as "buy" (trading periods during which according to the MA trading rule the investor's capital should remain invested in the market) and the mean return of the whole investment period; the mean return of individual trading periods characterized as "sell" (trading periods during which the investment capital should be liquidated or sold short) and the mean return of "buy" trading periods; or the mean return of "sell" periods and either the mean return of the whole investment period or zero.

Although on several occasions simple *t*-tests have been used to test for the statistical significance of such differences (e.g. Hudson et al. 1996; Wong et al. 2003), strictly speaking the application of the *t*-test which assumes normal, stationary, and time-independent distributions is not legitimate since one or more of these assumptions is very often violated in asset returns (see for example Mills 1991). To overcome this problem, bootstrapping techniques have been suggested by Brock et al. (1992) and this approach has been recognized as the established one and is used by most authors (e.g. Bessembinder and Chan 1991; Mills 1997; Kwon and Kish 2002; Fong and Yong 2005).

In this paper an alternative testing procedure for assessing the predictive performance of the MA trading rule is suggested and it is argued that it has some considerable advantages over the existing one. In principle the proposed approach allows for the concurrent estimation of measures of the predictive power of the MA trading rule, such as the ones mentioned above, and at same time taking into consideration the interdependence in asset returns.

The rest of the paper is structured as follows: in section 2, the basic points of the proposed alternative methodology are explained; in section 3, the results of the empirical analysis for daily data of the FT-30 Index of the London Stock Exchange are presented, discussed and compared with those of other studies; section 4 summarizes and concludes the paper.

2. Methodology and data

The intended testing procedure is a modification of the so-called impact assessment models originally developed by Box and Tiao (1975). By the term impact assessment is meant a test of the null hypothesis that an event caused a change in a stochastic process measured by a time series. Events (also called “interventions” in the time series literature) may be represented by binary variables. However, the standard parametric or non-parametric statistical tests which are used to test differences in levels (e.g. the *t*-test, ANOVA, etc.) cannot be used in serially correlated data, as the fundamental assumption of independence among observations is violated. Moreover, a change in level may not take place instantaneously but gradually. For the inadequacy of the *t*-test for such cases see for instance Abraham (1980). A method of impact assessment which takes into account serial correlation, as well as gradual level shifts has been suggested by Box and Tiao (1975) and allows for simultaneous maximum likelihood estimation of the parameters related to the level change as well as those related to the serial correlation. Hence, it can be considered as a generalization of the *t*-test.

The original methodology consists on the following steps:

i) Definition of the event and exact identification of its onset.

ii) Univariate ARIMA model-building for the time series under consideration.

iii) Inclusion of (an) intervention component(s), and re-estimation of the full model.

If the time series under consideration is represented by W_t, impact assessment models are of the following general form:

$$Y_t = f(\vec{k}, \vec{I}_t) + N_t \tag{1}$$

where,

$Y_t = W_t$ itself, or some transformation of W_t to ensure variance stationarity (see Milionis 2004),

$f(\vec{k}, \vec{I}_t)$ measures the effect(s) of the external event(s),

$\vec{k}$ is the vector of intervention parameters,

$\vec{I}_t$ is the vector of intervention variables,

N_t is the, generally coloured, noise component.

The noise component is described by an ARIMA model (Box and Jenkins 1976) of the following form:

$$\Phi(\mathrm{B})N_t = c + \Theta(\mathrm{B})\alpha_t$$

where:

α_t is white noise,

c is a constant,

B is the backward shift operator,

$\Phi(\mathrm{B}) = 1 - \varphi_1 \mathrm{B} - \ldots - \varphi_p \mathrm{B}^p$ is the so-called autoregressive polynomial of order p in B,

$\varphi_1, \varphi_2, \ldots, \varphi_p$ are constant coefficients,

$\Theta(\mathrm{B}) = 1 - \theta_1 \mathrm{B} - \ldots - \theta_q \mathrm{B}^q$ is the so-called moving average polynomial of order q in B,

$\theta_1, \theta_2, \ldots, \theta_q$ are constant coefficients.

If the process N_t is integrated of order d then $\Phi(\mathrm{B})$ can be made stationary by differencing d times so that:

$$\Phi(\mathrm{B}) = \varphi(\mathrm{B})(1 - \mathrm{B})^d$$

with the all the roots of $\varphi(\mathrm{B})$ outside the unit circle.

I_t can be either a pulse (i.e. equals one at $t = \mathrm{T}$ (where T is the time that the intervention occurs) and zero elsewhere), or a step function (i.e. equals zero, before $t = \mathrm{T}$ and one for t greater or equal to T).

The vector of intervention parameters $\vec{k}$ can be expressed in terms of the vectors $\vec{\omega}$, $\vec{\delta}$ as follows (Box and Tiao 1975):

$$f(\vec{k}, \vec{I}_t) = f(\vec{\omega}, \vec{\delta}, \vec{I}_t) = \frac{\Omega(\mathrm{B})}{\delta(\mathrm{B})} I_t \qquad (2)$$

where:

$\Omega(\mathrm{B}) = \omega_0 + \omega_1 \mathrm{B} + \ldots + \omega_r \mathrm{B}^r$,

$\delta(\mathrm{B}) = 1 - \delta_1 \mathrm{B} - ... - \delta_s \mathrm{B}^s$ and

$\omega_0, \omega_1, ..., \omega_r, \delta_1, \delta_2, ..., \delta_s$ are constant parameters following certain restrictions (Box and Tiao 1975).

The $\Omega(\mathrm{B})$ polynomial reflects the total change in the level of asset returns caused by the binary series I_t, while the $\delta(\mathrm{B})$ polynomial expresses the rate at which asset returns approach a new equilibrium level due to the effect of I_t.

The intervention parameter estimates ω_i, δ_i and the stochastic parameter estimates φ_i, θ_i are asymptotically independent of each other (Box et al. 1994), hence, the information matrix is block-diagonal. The inverse of the information matrix can be used as an estimator of the asymptotic covariance matrix of the parameter estimates. The estimates of both the intervention and the noise parameters can be obtained simultaneously by maximum likelihood (details in Box and Tiao 1975).

Thus far the method has been used to study the effect of events which occur on continuous lags. However, if the effect of such events is assumed to be transient, then their impact can also be examined in cases where events tend to occur discontinuously. For the case of such discontinuous impacts, the values of the parameter vectors $\vec{\omega}$, $\vec{\delta}$ will reflect the average effect of the factor which acts discontinuously on a time series.

In this work the Box and Tiao (1975) methodology, with the modifications described above, will be applied to examine, whether or not, the moving average trading rule has predictive power for the FT-30 Index of the London Stock Exchange using daily closing prices for the period 1935-1994. This can be performed in the following way: as explained in the previous section, the role of the MA trading rule is to classify each individual trading period (in this case each individual day) as "buy" or "sell". The "buy" days will be considered as the discontinuous interventions. Therefore, the intervention variable I_t will be a binary series of "1" and "0" corresponding to the "buy" and "sell" days respectively. It is noted that the time origin for which the intervention variable will be assigned its first value (i.e. a "1" or a "0") is the period (day) at which the MA trading rule generates its first signal, which is apparently equal to the length of the long moving average considered each time.

The total time period that the data set considered in this work cover approximately coincides with that of previous studies of other scholars (e.g. Mills 1997; Markellos 1999) who examined the predictive performance of the MA trading rule for the same stock exchange index, but using different techniques. This will make it possible to directly compare the results derived following the statistical approach suggested above with those of the previous studies. The total time period, will be divided into three 20-year sub-periods: 1935-1954, 1955-1974 and 1975-1994 and each sub-period will also be examined. The particular combinations of long and short moving averages for the application of the moving average trading rules which will be employed are deliberately taken to coincide with those of the previous studies and are the following: 1-50, 1-150, 5-150, 1-200 and 2-200, where the first number indicates the length of the short moving average and the second number, the length of the long moving average.

3. Empirical analysis

At first it is useful to present and comment on some summary descriptive statistics relating to the data set. Such statistics are shown in Table 1, which refer to the daily returns of the FT-30 Index expressed as logarithmic differences of successive closing prices of the Index. From the results of Table 1, it is evident that over the whole period, as well as in any sub-period, index returns are non-normal, asymmetric (negatively skewed) and leptokurtic, as is also found in Mills (1997). Further, the first order autocorrelation coefficient for index returns ($\rho(1)$) is significant at 5% level for the whole period, as well as for all sub-periods (it is noted, however, that significance testing for autocorrelations should be taken as indicative but not exact, for index returns are not normal, as documented above). In addition, 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 $\mathrm{AR}(1)$ model of index returns. Again higher-than-first-order autocorrelation, which is significant at the 5% level exists for all time periods, is present. Moreover, there is strong evidence of substantial interdependence in the squares of index returns, as the last two columns of Table 1 reveal. The existence of such interdependence in higher moments of index returns is a necessary condition for the existence of trading rule abnormal returns (Neftci 1991).

As will become evident below, it is to the methodological benefit of the empirical analysis if any linear dependencies in index returns are initially disregarded, i.e. if it is assumed that N_t in Eq. (1) is white noise. It will be further assumed that in Eq. (2) above $r = s = 0$, so that $\Omega(\mathrm{B}) = \omega_0$ and $\delta(\mathrm{B}) = 1$.

Combining Eq. (1) and Eq. (2) and taking the above assumption into consideration it is easily seen that index returns may be described by the following model:

$$R_t = c + \omega_0 I_t + a_t \tag{3}$$

In Eq. (3) the parameter ω_0 represents the relative average increase (if any) on returns during the "buy" periods, as compared to the "sell" periods, while the parameter c represents the average return of "sell" days. Therefore, results on the statistical significance of the parameter ω_0 may be directly compared with the results from an ordinary *t*-test for the mean difference of "buy-sell" for index returns, while testing for the statistical significance of parameter c corresponds to the ordinary *t*-test for the statistical significance of the mean return of "sell" days. It must be noted, however, that it is preferable to use Eq. (3) to test the significance of these measures of trading rule predictability rather than to use two distinct *t*-tests, since with the use of Eq. (3) both c and ω_0 are estimated and tested concurrently.

The model represented by Eq. (3) will be called the "benchmark" model henceforth. It is apparent that the "benchmark" model is simply a linear regression model with a dummy explanatory variable and it is stressed that this model will only be used for the sake of comparisons, as from the results of autocorrelation in Table 1 it is evident that the residuals of this model are expected to be autocorrelated and, hence, strictly speaking, any significance testing of model parameters under such circumstances is not valid.

The effect of linear dependencies in index returns, which do exist as evidenced by the results of Table 1, may be taken into account by considering the model:

$$R_t = c + \omega_0 I_t + \frac{\Theta(\mathrm{B})}{\Phi(\mathrm{B})} a_t \tag{4}$$

This model will be called the "full" model henceforth and the new estimates of c and ω_0 will be purged of the effect of linear interdependencies in index returns.

Univariate ARMA models for index returns in each case must be created. This is useful not only because ARMA models can be used as a first step in the model building of an impact assessment model, but also because in that way it will be possible to assess the improvement in the explanatory power of the "full" models, which will include the intervention parameters, in comparison to that of the univariate models. The model building procedure followed for the creation of the univariate models for each time period is the one suggested by Box and Jenkins (1970, 1976). Both the pattern of the autocorrelation function, as well as that of the partial autocorrelation function, in all cases was suggestive of clearly stationary index returns. Moreover, pure moving average processes of order greater than one were preferable to purely autoregressive, or mixed processes (further details are available from the authors on request). Though this is in accordance with the empirical findings of other studies (e.g. Milionis et al. 1998), it differs from the empirical finding of Mills (1997) who fits $\mathrm{AR}(2)$ or even $\mathrm{AR}(1)$ models to almost identical data. In the course of the empirical analysis of this study, $\mathrm{AR}(2)$ models did not render white noise residuals. It is noted, however, that conditional heteroscedasticity which, according to the results of Table 1 is also present in the data, has not been taken into consideration in this study.

The results of the empirical analysis, based on the parameter estimates using the "benchmark" model as well as the "full" model, for the total time period and each sub-period, for all trading rules are presented in Tables 2 to 5. Together with the values and the associated *t*-statistics for the parameters c and ω_0 the results from ordinary *t*-tests are also quoted in these tables. Additional pieces of information also included in each of the Tables 2 to 5 are the values of the coefficient of determination (R^2) for the univariate models as well as the "full" models. The value of this coefficient is directly related to the degree of linear interdependencies in the index returns series; hence it may be taken as a measure of the departure from randomness; the latter is among the fundamental assumptions for the application of the *t*-test. Moreover, the value of R^2 will also be useful in assessing the improvement in the explanatory power of the models describing index returns due to the separation of returns into "buy" and "sell" returns, as a result of the application of the MA trading rule.

Based on the results presented in Tables 2 to 5 the following interesting remarks can be made:

(a) For all time periods the values of the parameters c and ω_0 derived by using the "benchmark" model (columns (1), (2)) are identical to the corresponding values for the mean return of "sell" days and the mean "buy–sell" difference respectively, as is evident from the results for the ordinary *t*-test (columns (7) and (8) respectively).

(b) Though the *t*-statistics associated with the ω_0 parameter (column (2)) are almost identical to those reported in the results of the *t*-test for the significance of the "buy–sell" difference for all time periods (column (8)), the *t*-statistics associated with the parameter c (column (1)) imply slightly lower standard errors for c as compared to the standard errors associated with the ordinary *t*-test for the significance of the mean return of "sell" days (column (7)). This small difference is due to the concurrent estimation of both parameters obtained by using the "benchmark" model and could be attributed to the fact that a small part of the variation in index returns in explained by the binary explanatory variable of the "benchmark" model.

(c) It is of importance to compare the estimates as well as the associated *t*-statistics of the parameters c and ω_0 derived from the "benchmark" model (columns (1) and (2)) and the "full" model (columns (3), (4)). In all cases, except for the last sub-period, the estimates of c are less negative with the "full" model than with the "benchmark" model. On the other hand, the estimates of ω_0 are always less positive with the "full" model than with the "benchmark" model. This is due to the effect of autocorrelation which is incorporated in the "full" model, but not in the "benchmark" model. The effect is most pronounced in the first sub-period. This can be is easily confirmed by the comparison of the estimates of c and ω_0 derived by each model for the total time period (Table 2) and the first sub-period (Table 3). Indeed, while the estimates of c obtained using the "benchmark" model for all trading rules are less negative for the total time period, with the "full" model it is the other way round. Similarly, the ω_0 estimates with the "benchmark" model for all cases are more positive for the first sub-period, but with the "full" model it is the other way round. This can be easily explained by looking at the R^2 values of the univariate model in each time period (column 6). The first sub-period has by far the highest R^2 value, hence, the effect of autocorrelation is expected to be the highest for this time period.

(d) Despite the differences in the results of the "benchmark" and the "full" model, it is apparent that in all time periods qualitatively the conclusions regarding the predictive power of the trading rules are by and large the same. Of particular importance is the fact that although for the first two sub-periods (1935-1954 and 1955-1974) the hypothesis of weak form efficiency is rejected by most trading rules, for the last sub-period (1975-1994) the hypothesis of weak form efficiency is not rejected in all but one tests.

It also of great interest to compare the results of this study with those of other studies, which used data of the same time period but followed different methodological approaches. More specifically, Mills (1997) followed the established bootstrapping approach, while Markellos (1999) suggested and used the co-integration cumulative profit (CCP) test. To facilitate comparisons, the results for each time period of the three different methodologies have been gathered together and are presented in Tables 6 to 9.

Examination of Tables 6 to 9 shows that all methodologies agree that there is a pronounced weakening of the predictive power of the trading rule in the last sub-period (1975-1994). Moreover, the results for the significance testing of the ω_0 parameter (i.e. the “buy-sell” difference) of this study agree completely with those of Mills (1997) for all time periods and trading rules. In addition, the results for the significance testing of the c parameter (mean return for “sell” days) of this study are quite similar, yet not identical, with those of Mills (1997). Direct comparison regarding these parameters with the results of Markellos (1999) is not possible as the approach followed by the latter is based on a different reasoning. Qualitatively however, it is evident that all methodologies, by and large, agree in their conclusions regarding the predictive performance of the MA trading rule and that the results of this study are somewhat closer to those of Mills (1997) as compared to those of Markellos (1999).

4. Summary and conclusions

In this work an alternative statistical approach for the assessment of the predictive power of the moving average trading rule in financial markets is suggested. This approach is a modification of the impact assessment stochastic models originally introduced by Box and Tiao (1975). With the proposed methodology, measures of predictive power of the trading rule such as the mean value of the “sell” periods and the mean “buy-sell” difference can be concurrently estimated and tested for their statistical significance, but at the same time controlling for autocorrelation in asset returns. Application of this approach to the daily closing prices of the FT-30 Index of the London Stock Exchange gave results very similar to those of the established methodology (bootstrapping) and similar to other alternative methods (cointegration cumulative profit test). In particular, the results of the proposed methodology provide evidence of a pronounced weakening of the predictive power of the MA trading rule for the last sub-period (1975-1994), which implies non-rejection of the weak form market efficiency hypothesis, confirming the findings of other methods. In general, however, abnormal returns attributed to the predictive power of the trading rule are found to be clearly smaller than those estimated by ordinary *t*-tests.

Among the advantages of the proposed approach is that it is less computationally intensive than bootstrapping. Moreover, with the proposed approach the conclusion regarding the predictive power of the moving average trading rule is expressed at a higher measurement level than with the existing methodologies (quantitative versus categorical).

The proposed methodology may be enhanced further, as it is susceptible to several improvements at both the technical and practical level. As a first step, the problem with non-normal distributions in asset returns may be alleviated by considering the more general class of GED distributions for the testing procedure. Further, second order dependencies in asset returns such as conditional heteroscedasticity may also be taken into account by considering a general ARMA-GARCH model for the noise component of the impact assessment model. Finally, higher order intervention parameters may be estimated. That entails that returns during the "buy" periods may not be assumed constant, as is the case with any of the existing methodologies, but could follow a more flexible pattern, something that is consistent with the principles of technical analysis (e.g. Pring 1991). This may have important practical implications, as it may result in improved trading strategies and performance. Hence, overall the proposed methodology seems promising and potentially has some considerable advantages as compared to the established ones.

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Appendix

TABLE 1 Summary statistics for daily index returns[1].

Time period	mean* 10^{-4}	std	skewness	kurtosis	KS-test	autocorrelation: Returns $\rho(1)$	autocorrelation: Returns LBQ(10) (in res. of AR(1) model)	autocorrelation: Squared Returns $\rho^2(1)$	autocorrelation: Squared Returns LBQ(10) (in res. of AR(1) model)
1935-1994	2.1912 (**) (2.67)	0.01004	-0.1438	11.5320	0.4816 (**)	0.0983 (**)	72.44 (**)	0.42025 (**)	431.06 (**)
1935-1954	1.3056 (1.52)	0.0060	-0.4332	17.1266	0.4879 (**)	0.3441 (**)	47.24 (**)	0.2921 (**)	437.39 (**)
1955-1974	0.1103 (0.07)	0.0102	-0.1844	10.3541	0.4826 (**)	0.0953 (**)	30.13 (**)	0.3886 (**)	88.44 (**)
1975-1995	5.2711 (**) (2.94)	0.0126	-0.0956	7.4298	0.4794 (**)	0.0464 (**)	45.12 (**)	0.4324 (**)	169.20 (**)

[1] The Kolmogorov-Smirnov (KS-test) critical value is 0.0110 (5%). X_9^2 critical values (for LBQ-statistic): 14.68 (10%), 16.91 (5%). One asterisk (*) indicates significance at 10% level. Two asterisks (**) indicate significance at 5% level.

TABLE 2 Results for the 1935-1994 time period (*t*-statistics in parentheses)[2].

Trading Rule	"benchmark" model		"full" model			Univariate ARIMA Model	Ordinary *t*-test	
	$c \cdot 10^{-3}$	$\omega_o \cdot 10^{-3}$	$c \cdot 10^{-3}$	$\omega_o \cdot 10^{-3}$	R^2	R^2	Mean "sell"$\cdot 10^{-3}$	Mean "buy-sell" difference$\cdot 10^{-3}$
1-50	-0.437 (**) (-3.40)	1.111 (**) (6.64)	-0.241 (-1.64)	0.778 (**) (4.00)	0.0170	0.0161	-0.437(**) (-3.06)	1.111 (**) (6.64)
1-150	-0.164 (-1.23)	0.611 (**) (3.60)	-0.038 (-0.02)	0.346 (**) (2.81)	0.0169	0.0161	-0.164 (-1.08)	0.612 (**) (3.60)
5-150	-0.054 (-0.41)	0.434 (**) (2.55)	0.054 (0.34)	0.309 (**) (2.47)	0.0169	0.0161	-0.054 (-0.36)	0.435 (**) (2.55)
1-200	-0.170 (-1.25)	0.611 (**) (3.57)	-0.026 (-0.17)	0.362 (**) (2.96)	0.0174	0.0165	-0.170 (-1.11)	0.611 (**) (3.56)
2-200	-0.123 (-0.91)	0.538 (**) (3.14)	-0.019 (-0.12)	0.373 (**) (2.83)	0.0174	0.0165	-0.123 (-0.81)	0.538 (**) (3.14)
Column number	1	2	3	4	5	6	7	8

[2] One asterisk (*) indicates significance at 10% level. Two asterisks (**) indicate significance at 5% level.

TABLE 3 Results for the 1935-1954 time period (*t*-statistics in parentheses)[3].

Trading Rule	"benchmark" model		"full" model			Univariate ARIMA Model	Ordinary *t*-test	
	$c \cdot 10^{-3}$	$\omega_0 \cdot 10^{-3}$	$c \cdot 10^{-3}$	$\omega_0 \cdot 10^{-3}$	R^2	R^2	Mean "sell"$\cdot 10^{-3}$	Mean "buy-sell" difference $\cdot 10^{-3}$
1-50	-0.619 (**) (-4.49)	1.219 (**) (6.93)	-0.208 (-1.07)	0.331 (**) (2.19)	0.1353	0.1337	-0.619 (**) (-3.40)	1.219 (**) (6.89)
1-150	-0.329 (**) (-2.33)	0.708 (**) (3.96)	-0.180 (-1.00)	0.278 (**) (2.00)	0.1367	0.1356	-0.329(*) (-1.75)	0.708(**) (3.96)
5-150	-0.172 (-1.22)	0.456 (**) (2.55)	-0.258 (-1.43)	0.322 (**) (2.32)	0.1370	0.1356	-0.171 (-0.92)	0.455(**) (2.54)
1-200	-0.322 (**) (-2.25)	0.688 (**) (3.82)	-0.201 (1.11)	0.287 (**) (2.08)	0.1383	0.1371	-0.322 (*) (-1.67)	0.688 (**) (3.81)
2-200	-0.303 (*) (-1.85)	0.660 (**) (3.67)	-0.280 (*) (-1.66)	0.313 (**) (2.06)	0.1388	0.1371	-0.304 (-1.57)	0.6601 (**) (3.67)
Column number	1	2	3	4	5	6	7	8

[3] One asterisk (*) indicates significance at 10% level. Two asterisks (**) indicate significance at 5% level.

TABLE 4 Results for the 1955-1974 time period (*t*-statistics in parentheses)[4].

Trading Rule	"benchmark" model		"full" model			Univariate ARIMA Model	Ordinary *t*-test	
	$c \cdot 10^{-3}$	$\omega_0 \cdot 10^{-3}$	$c \cdot 10^{-3}$	$\omega_0 \cdot 10^{-3}$	R^2	R^2	Mean "sell"$\cdot 10^{-3}$	Mean "buy-sell" difference$\cdot 10^{-3}$
1-50	-0.519 (**) (-2.62)	1.058 (**) (3.62)	-0.445 (*) (-1.84)	0.834 (**) (2.51)	0.0230	0.0219	-0.517(**) (-2.28)	1.057 (**) (3.61)
1-150	-0.503 (**) (-2.30)	0.925 (**) (3.14)	-0.441(**) (-1.96)	0.786 (**) (2.38)	0.0224	0.0211	-0.503 (**) (-2.03)	0.925 (**) (3.14)
5-150	-0.458 (**) (-2.10)	0.843 (**) (2.86)	-0.445(*) (-1.87)	0.783 (**) (2.36)	0.0224	0.0211	-0.458 (*) (-1.86)	0.843 (**) (2.86)
1-200	-0.527 (**) (-2.41)	0.985 (**) (3.33)	-0.476 (**) (-2.00)	0.892 (**) (2.77)	0.0220	0.0210	-0.528(**) (-2.15)	0.985 (**) (3.33)
2-200	-0.489 (**) (-2.23)	0.913 (**) (3.08)	-0.462 (**) (-1.96)	0.868 (**) (2.68)	0.0220	0.0210	-0.489 (**) (-1.99)	0.913 (**) (3.08)
Column number	1	2	3	4	5	6	7	8

[4] One asterisk (*) indicates significance at 10% level. Two asterisks (**) indicate significance at 5% level.

TABLE 5 Results for the 1975-1994 time period (*t*-statistics in parentheses)[5].

Trading Rule	"benchmark" model		"full" model			Univariate ARIMA Model	Ordinary *t*-test	
	$c \cdot 10^{-3}$	$\omega_0 \cdot 10^{-3}$	$c \cdot 10^{-3}$	$\omega_0 \cdot 10^{-3}$	R^2	R^2	Mean "sell"$\cdot 10^{-3}$	Mean "buy-sell" difference$\cdot 10^{-3}$
1-50	-0.011 (-0.04)	0.958 (**) (2.62)	0.341 (1.02)	0.705 (**) (2.61)	0.0117	0.0106	-0.011 (-0.04)	0.958 (**) (2.61)
1-150	0.388 (1.21)	0.054 (0.15)	0.602 (1.45)	-0.259 (-0.64)	0.0050	0.0047	0.389 (1.17)	0.053 (0.15)
5-150	0.517 (1.54)	-0.135 (-0.38)	0.682 (1.62)	-0.376 (-0.94)	0.0051	0.0047	0.517 (1.59)	-0.135 (-0.37)
1-200	0.481 (1.49)	-0.030 (-0.08)	0.571 (1.56)	-0.158 (-0.41)	0.0055	0.0054	0.481 (1.38)	-0.030 (-0.08)
2-200	0.552 (*) (1.73)	-0.132 (-0.37)	0.641 (*) (1.88)	-0.259 (-0.67)	0.0055	0.0054	0.552 (*) (1.66)	-0.132 (-0.37)
Column number	1	2	3	4	5	6	7	8

5 One asterisk (*) indicates significance at 10% level. Two asterisks (**) indicate significance at 5% level.

TABLE 6 Comparative results for the 1935-1994 time period[6].

Trading Rule	This study		Mills (1997)		Markellos (1999)
	c	ω_0	*c*	ω_0	CCP test
1-50	NS	**	∅	∅	**
1-150	NS	**	∅	∅	**
5-150	NS	**	∅	∅	**
1-200	NS	**	∅	∅	**
2-200	NS	**	∅	∅	**

[6] One asterisk (*) indicates significance at 10% level. Two asterisks (**) indicate significance at 5% level. NS denotes no statistical significance at 10%level. ∅ denotes no available results. CCP stands for co-integration cumulative profit test.

TABLE 7 Comparative results for the 1935-1954 time period[7].

Trading Rule	This study		Mills (1997)		Markellos (1999)
	c	ω_0	c	ω_0	CCP test
1-50	NS	**	**	**	NS
1-150	NS	**	**	**	**
5-150	NS	**	∅	∅	**
1-200	NS	**	*	**	**
2-200	*	**	∅	∅	**

[7] One asterisk (*) indicates significance at 10% level. Two asterisks (**) indicate significance at 5% level. NS denotes no statistical significance at 10%level. ∅ denotes no available results. CCP stands for co-integration cumulative profit test.

TABLE 8 Comparative results for the 1955-1974 time period[8].

Trading Rule	This study		Mills (1997)		Markellos (1999)
	c	ω_0	c	ω_0	CCP test
1-50	*	**	**	**	**
1-150	**	**	∅	∅	**
5-150	*	**	**	**	**
1-200	**	**	**	**	**
2-200	**	**	∅	∅	**

[8] One asterisk (*) indicates significance at 10% level. Two asterisks (**) indicate significance at 5% level. NS denotes no statistical
significance at 10%level. ∅ denotes no available results. CCP stands for co-integration cumulative profit test.

TABLE 9 Comparative results for the 1975-1994 time period[9].

Trading Rule	This study		Mills (1997)		Markellos (1999)
	c	ω_0	c	ω_0	CCP test
1-50	NS	**	NS	**	NS
1-150	NS	NS	NS	NS	**
5-150	NS	NS	∅	∅	NS
1-200	NS	NS	NS	NS	NS
2-200	NS	NS	∅	∅	NS

[9] One asterisk (*) indicates significance at 10% level. Two asterisks (**) indicate significance at 5% level. NS denotes no statistical significance at 10%level. ∅ denotes no available results. CCP stands for co-integration cumulative profit test.

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