NON LINEAR DIACHRONIC INTERACTION BETWEEN THE ADVANCE / DECLINE RATIO INDEX AND THE RETURNS OF THE MAPKET'S GENERAL INDEX: EMPIRICAL EVIDENCE FROM THE ATHENS STOCK EXCHANGE.

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ABSTRACT

This paper examines the existence of a linear or nonlinear interaction between the Advance/Decline ratio index and the returns of the Athens General Index. We investigate the possibility of a nonlinear causality mechanism through which the Advance/Decline ratio index (the ratio of the number of shares whose price increased over those that declined) may affect the returns of the Athens General Index and vice versa. The statistical evidence derived from linear and nonlinear causality tests indicate that there is indeed a bidirectional nonlinear causality between these two indexes.

Keywords: Advance/Decline ratio index ,General Index, Linear and Nonlinear Granger Causality.

JEL classification: G14

1. Introduction.

This short paper examines the diachronic interaction between the Advance/Decline ratio index (henceforth A/D index) and the returns of the General Index of the Athens Stock Exchange (GI). More specifically, it investigates the existence of a linear or nonlinear causality mechanism by which the A/D ratio index may affect stock returns and vice versa.

The A/D index is the ratio of the number of stocks that closed higher to those that declined in value for a particular trading day and it is widely accepted as an indicator of market strength. It is published daily along with other market data and it has been adopted by many technical analysts to support their technical analysis charts. Whether or not one agrees with technical analysis methodologies and predictions, the A/D index does represent useful information that is published daily[1] by the Exchange. We can formulate two hypotheses regarding the meaning / representation of the A/D index: according to the first one, $H_{0,}$ the ratio reflects the dynamics of the market during a given day and any information available to market participants is expressed simultaneously in both the General Index and the A/D index. If this hypothesis holds, then we should not expect to find a causal relationship from the General Index to the A/D index or vice versa. This hypothesis is consistent with the efficient markets hypothesis.

According to the second, H_1, the A/D ratio of a given day is interpreted by investors as a signal of market strength and will induce them to expand their investments, in anticipation of further gains, which is expressed by stronger demand for shares the following day. If this hypothesis holds, therefore, we should find a causal relationship (linear or non-linear) with causality going from the A/D ratio to the index. The reverse could be also valid, if we accept that the percentage change (return) of the General Index can have an impact on investor's sentiment and expectations which is expressed the following day with changes in the demand/ supply of stocks. Generally speaking, the H1 is consistent with a market dominated not by professional day traders who would react instantaneously to any new information, but by less sophisticated investors who usually wait until the close of the market to form their investment decisions for the following trading day (s).

The purpose of this short paper is to investigate the existence of a bidirectional nonlinear causality between the Advance/Decline ratio index and stock returns as measured by the GI, using the standard linear causality procedure of Hsiao's (1981) with the help of the Box-Cox transformation, and to provide analytical and empirical evidence on the subject.

The remainder of this paper is organized as follows: Section 2 describes the data sets and the methodology used in this study, while Section 3 presents the empirical results. Finally, Section 4 provides a summary of the main findings and presents the conclusions of this study.

[1] Obviously, the index can be calculated intraday- real time.

2. The data and methodology employed.

This study uses daily returns of the General Index[2] (GI) of the Athens Stock Exchange (ATHEX) and the levels of the Advance/Decline ratio index which is defined as:

$$(A/D)_t = \frac{(Advance \quad Issues)_t}{(Decline \quad Issues)_t} \qquad (1)$$

The period under examination is from 07/01/1999 to 10/5/2006, giving us a total of 1835 observations for each series. The GI is adjusted for dividends, stock splits and reverse stock splits. Finally, in all cases, the logarithmic transformation of the original series is used. Although the time period we chose to investigate is somewhat arbitrary, it is long enough for the statistical techniques to be valid and it includes periods of strong growth, stagnation and decline. Moreover, for most of this period, (as of 2001) the Athens Stock Exchange was re-classified from an emerging to a mature market and daily trading volumes were significant.

Before we applied the causality tests, we investigated the order of integration of the available data using Augmented Dickey Fuller (ADF) and PP tests for unit roots.

Table 1. **Results of Unit Root Tests.**

	Levels		**First Differences**				
Variables	**DF**	**PP**	**DF**	**PP**	**1%**	**5%**	**10%**
General Index Returns.	-0.3939[2]	-0.7338	-4.6131[1]	-6.369	-4.26	-3.55	-3.208
Advance Decline Ratio	-0.9709[2]	-1.7670	-5.8760[1]	-6.896	-4.26	-3.55	-3.208

DF, PP denotes the Dickey - Fuller and Phillips - Perron unit root tests respectively. The PP test is calculated with a lag length equal to 3. Figures in square brackets denote the number of lagged dependent variables in the regression. The selection between zero and non-zero lags was based on the Akaike information Criterion (AIC). The test of the entries are the values of the unit root test, the critical values of which are - 4.26, - 3.55 and - 3.208 at 1% , 5% and 10% significance level for T = 33. The results of Table 1 tend to suggest[3] that these two variables are stationary.

[2] The General Index of the ASE is calculated by the Exchange itself and is intended to represent overall market trends. The GI includes 60 stocks, weighted according to their participation in total market capitalization and it is revised twice a year. Obviously, large cap stocks have a strong weight (the largest one has a 10% weight) and affect the index accordingly, however stocks from all industries and mid-cap stocks are included in the GI.

[3] Using the Engel_Granger cointegration approach we didn't find any long run relation between these variables. Detailed results are available on request by the author.

To test series for nonlinear[4] causality, a transformation of Hsiao's (1981) linear causality test was used in our analysis. The test is based on a bivariate VAR representation for two stationary series χ_t and y_t. The suggested procedure for non linear causality is based on the bivariate VAR representation:

$$x(\lambda))_t = \alpha_0 + \sum_{i=1}^{n_1} \alpha_i x(\lambda)_{t-i} + \sum_{j=1}^{q_1} \beta_j y(\lambda)_{t-j} + \varepsilon_{x,t} \quad (1)$$

$$y(\lambda)_t = \beta_0 + \sum_{i=1}^{n_2} \alpha_i x(\lambda)_{t-i} + \sum_{j=1}^{q_2} \beta_j y(\lambda)_{t-j} + \varepsilon_{y,t} \quad (2)$$

with

$$y_t(\lambda) = \frac{y_t^{\lambda} - 1}{\lambda} \quad \text{and} \quad x_t(\lambda) = \frac{x_t^{\lambda} - 1}{\lambda} \quad \text{where } \lambda \in (0,+1) \quad (3)$$

and

$$y_{(\lambda)} = \log y \quad \text{and} \quad \chi_{(\lambda)} = \log x \qquad \lambda \Rightarrow 0 \qquad (4)$$

where $x_t(\lambda)$ and $y_t(\lambda)$ are stationary variables and n_1, n_2 and q_1,q_2 are the lag lengths of $\chi_t(\lambda)$ and $y_t(\lambda)$ respectively. The null hypothesis in the Granger causality test is that $y_t(\lambda)$ does not cause $\chi_t(\lambda)$ which is represented by H_0: $\beta_1=\beta_2=...\beta q=0$ and the alternative hypothesis is H_1:$\beta \neq 0$ for at least one j in Equation (1). The test statistic has a standard F distribution with (n, T-n-q-1) degrees of freedom, where T is the number of observations. Akaike (1969) final prediction error (FPE)[5] is used to find the optimal lag lengths for both $\chi_t(\lambda)$ and $y_t(\lambda)$

As in Hsiao (1981), we suggested a sequential procedure for testing non linear causality, for different values of the parameter λ, that combines Akaike's final predictive error criterion (FPE) and the definition of Granger causality. To test for causality from $y_t(\lambda)$ to $x(\lambda)$, the procedure consists of the following steps:

1. Treat $\chi_t(\lambda)$ as a one-dimensional process as represented by Eq. (1) with $\beta_j = 0 \quad \forall$ j, and compute its FPE with n varying from 1 to L, which is chosen arbitrarily. Choose the n that gives the smallest FPE, denoted FPE_x(n, 0).

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[4] Baek and Brock (1992) proposed a nonparametric method for detecting nonlinear dynamic causal relations between two time series. This method was modified by Hiemstra and Jones (1994) to allow for weak temporal dependence. Unfortunelly a DOS version of this program didn't work in our computers.

[5] The FPE criterion is specified as follows: FPE=[(T+k)/(T−k)] (SSR/T) where T is the number of observations, k is the number of parameters estimated, and SSR is the sum of squared residuals.

2. ~~Treat χ_t (λ)~~ as a controlled variable, with n as chosen in step 1 and y_t (λ) as a manipulated variable as in Eq. (1). Compute the FPE's of Equation (1) by varying the order of lags of y_t (λ) from 1 to L and determine q, which gives true minimum FPE, denoted FPE_χ(n,q).

3. Compare FPE_χ(n, 0).) with FPE_x(n,q,). If the former is greater than the latter, or their ratio is greater than 1, then it can be concluded that y_t (λ) causes x_t (λ).

3. The Results.

In Table 2 we present the results of applying the linear[6] and nonlinear causality tests based on the specifications (1)-(4). As can be seen, using the suggested causality procedure we detect some form of causality in three out of the four possible cases we examine: unidirectional *linear* causality from the A/D ratio to the GI but not vice versa. On the other hand, using the same data set and different values of the Box-Cox coefficient, we detect a unidirectional *nonlinear* causality from the A/D ratio to the GI and visa versa .

Table 2. Direct Granger-causality test between the ATHENS Stocks Exchange General Index (GEN) and the ratio of Advance/Decline ratio index (FPE Results).

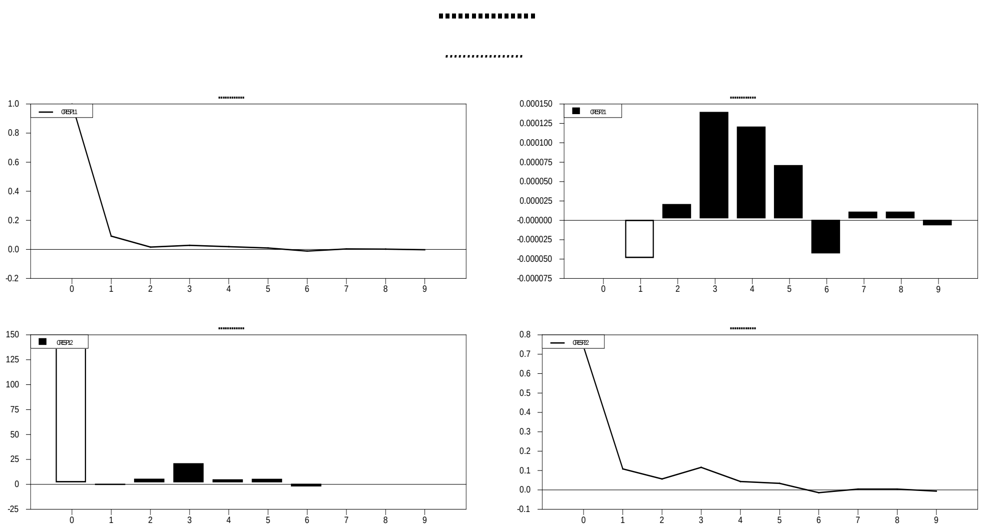
	LINEAR CAUSALITY	NONLINEAR CAUSALITY
Controlled Variable	Manipulated Variable	
	GEN_t	GEN_t
$(A/D)_t$	$\frac{FPE^{(A/D)(\lambda=1)}(n_1,{}^*0^*)}{FPE^{(A/D)(\lambda=1)}(n_1^*,q_1)}$ = 0.93538	$\frac{FPE^{(A/D)(\lambda=0.34)}(n_1,{}^*0^*)}{FPE^{(A/D)(\lambda=0.34)}(n_1^*,q_1)}$ = 1.01930
	$(A/D)_t$	$(A/D)_t$
GEN_t	$\frac{FPE^{GEN(\lambda=1)}(n_2,{}^*0^*)}{FPE^{GEN(\lambda=1)}(n_2^*,q_2)}$ = 1.03013	$\frac{FPE^{GEN(\lambda=0.34)}(n_1,{}^*0^*)}{FPE^{GEN(\lambda=0.34)}(n_1^*,q_1)}$ = 1.02900

Source : Our Results

The duration and the size of this feedback is given in Figure 1 below which presents the diachronic impulse pair wise responses, between the variables under examination.

[6] Assuming λ=1.

Figure 1 . Impulse pair wise responses, between the A/D ratio index and the returns of the Athens General Index.



From the table and the graph, we observe that the effect of the A/D index to the GI is stronger in both the linear and non linear versions, whereas the causal effect from the GI to the A/D ratio is weaker and in the linear model it is not detected at all.

Concluding this part, we present a series of results that refer to the predictional capacity of the models we used. It is advisable that whenever we test causality and linear or non-linear relationships are examined, at the same time the predictive ability of the models used should be tested, at least on a short term basis.

This is exactly what we did, using a repetitive random process where for random time periods we use the estimated parameters coming from the causality tests in order to perform predictions. These predictions are then compared to the actual data. The results are presented in Table 3 where our predictions refer to the correctly predicted direction of the GI for the next day, 2,3 and 4 days.

Table 3. Average General Index Forecasts.

	Linear causality		Non linear causality	
Predictions	Uniform direction of predictions	Non-uniform direction of predictions	Uniform direction of predictions	Non-uniform direction of predictions
1 day	0,5521	0,4479	0,5412	0,4588
2 days	0,2847	0,2103	0,2876	0,2623
3 days	0,1533	0,1163	0,1658	0,146
4 days	0,0858	0,0683	0,0996	0,0779

Source: our results.

As expected, the predictive ability is greater in all the one day predictions and, among the next day predictions, the uniform direction ones are most successful.

4. Conclusions.

In this study, we examined the possibility of a causal relationship between the Advance/Decline Ratio Index and the returns of the Athens Stocks Exchange General Index. The statistical evidence indicates that there is a bidirectional nonlinear causality between the A/D ratio index and the returns of the Athens General Index; that is, the lagged Advance/Decline ratio index cause, in a nonlinear Granger sense, the observed change in stock returns and vice versa. We therefore conclude that we reject the null hypothesis and we accept ~~the H1~~. This result is derived from an extension of the Hsiao's (1981) linear causality test using a Box-Cox transformation in order to test for nonlinear Granger causality.

Our results do not support the efficient markets hypothesis, at least in the context of the ATHEX market and during the specific period under examination. Our results can be interpreted as follows: in the short run, the simultaneous announcement of a positive (negative) A/D ratio along with positive (negative) returns of the GI affect the short term expectations of the investors, who interpret them as an indication of market strength, these expectations are then expressed as increased demand (offer) for shares, which cause the increase (decrease) in the returns of the General Index the following day. This investor behaviour, based on short term psychology rather than fundamentals, can explain the short term non linear causal relationship between the A/D ratio and the General Index of the Exchange.

References.

Akaike, Hirotugu, (1969), ‘Fitting autoregressive models for prediction’ Annals of the Institute of Statistical Mathematics 21, 243-247.

Akaike, Hirotugu, (1973), ‘A new look at the Statistical Model Selection.’ IEE Transactions on Automatic Control, 19, pp. 716-723.

Alexakis, P. and Petrakis, P., (1991), ‘Analysing Stock Market Behaviour in a Small Capital Market’, Journal of Banking and Finance, Vol.15, pp. 471-83.

Alexakis C, Niarchos N , Patra T and Pshakwale S., (2004), “The dynamics between stock returns and mutual fund flows: empirical evidence from the Greek Market”. Applied Financial Economics (2004), pp. 43–50.

Baek, E., & Brock, W., (1992) ‘A general test for nonlinear Granger causality: bivariate model’. Working Paper, Iowa State University and University of Wisconsin, Madison.

Brock, W., Hsieh, D.A. and Le Banon, B., (1991) ‘Nonlinear Dynamics, Chaos and Instability’ MIT Press, Cambridge, MA.

Cheng Hsiao, (1981), “Autoregressive Modelling and the Money-Income Causality Detection”, Journal of Monetary Economics, pp. 85-106

Cutler et al., (1989), “What moves stock prices”, Journal of Portfolio Management 15 pp. 4–12.

Caporale, Phillipas and Pitis, (2004). “Feedbacks between mutual fund flows and security returns: evidence from the Greek capital market”, Applied Financial Economics 14, pp-981-989.

DeLong, A. Shleifer, L.H. Summers and R.J. Waldmann, (1990), “Positive feedback investment strategies and destabilizing rational speculation”, Journal of Finance pp. 379–395.

Granger C and Moregenstern O., (1963), “Spectral analysis of New York stock prices”. Kyclos 16 pp. 1-27.

Hurvichm, C. M. and Tsai, C. (1993), "A Corrected Akaike Information Criterion for Vector Autoregressive Model Selection," Journal of Time Series Analysis, 14, 271 -279.

Hannan, E. J. and Quinn, B. G., (1979) “The determination of the order of an autoregressive”, Journal of the Royal Statistical Society, B41, 190–195.

Hiemstra, Craig and Jonathan Jones., (1994). "Testing for linear and nonlinear Granger Causality in the Stock Price-Volume Relation." Journal of Finance 5: 1639-1664.

Hsiao, Cheng. (1981). "Autoregressive Modeling and Money-Income Causal Detection." Journal of Monetary Economics, 7: 85-106.

Engle & Granger, R. (1987) Cointegration and error correction: Representation estimation and testing, Econometrica), pp. 251–276

Granger, (1969) , “Investigating causal relations by econometric methods and cross spectral”, Econometrica 37 pp. 24–36.

Granger, (1988), “Some recent developments in a concept of causality”, Journal of Econometrics 39, pp. 199–211.

Johansen, S. (1988), “Statistical analysis of cointegration vectors”, Journal of Economic Dynamics and Control 12 pp. 231–254.

Johansen, S. (1991), “Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive model”, Econometrica 59 pp. 1551–1580.

Johansen J. and K. Juselius, (1990) “Maximum likelihood estimation and inference on cointegration—with applications to the demand of money”, Oxford Bulletin of Economics and Statistics 52 pp. 169–210.

Karathanassis, G. and Philippas, N., (1993), ‘Heteroscedasticity in the Market Model: Some Evidence from the Athens Stock Exchange’, Managerial and Decision Economics, Vol. 14, pp. 563-567.

Koutmos et al.,(1993) “Stochastic behaviour of the Athens stock exchange”, Applied Financial Economics 3, pp. 119–126

Niarchos, N. (1972), The Greek stock market, Athens Stock Exchange Publications.

Niarchos & Alexakis, (1998), “Stock market prices, causality and efficiency: Evidence from the Athens stock exchange”, Applied Financial Economics 8, pp. 167–174

Panas, (1990) , “The behaviour of Athens stock prices”, Applied Economics 22 pp. 1715–1727.

Theil H. (1966), Applied Economic Forecasting, North-Holland, Amsterdam.