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SEMI-CHAOTIC FINANCIAL SERIES AND NEURAL NETWORK FORECASTING: EVIDENCE FROM EUROPEAN STOCK MARKETS

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Abstract: This study examines time series from five European Stock Markets (UK. Germany, Belgium, Spain and Greece). Based on empirical evidence concerning non-linear dependence, long-term memory effects and low-dimensional chaos, we assess the predictability of the series and determine the appropriate parameters for neural network modelling. We apply artificial neural network forecasting data sets from the semi-chaotic Greek Stock Exchange and utilise the outputs in the construction of a trading system. It is found that the neural network trading system performs significantly above random chance and other investment strategies.

Keywords: Chaos theory, R/S analysis, financial forecasting, artificial neural networks, European capital markets.

1. INTRODUCTION

Much of modern finance theory is driven by the assumption that any change in the rate of return of an asset must be caused by the arrival of unanticipated information about the future cash flows from the asset or the riskiness of these cash flows. This arrival of information is assumed to represent an exogenous shock, which is unrelated to past changes in the rate of return. Thus, time series of asset returns are considered as random walks and therefore information about past values is useless for predicting future values. Alternatively, a time series may be considered to be generated by a deterministic process, in which each element is exactly generated by previous elements.

Under certain circumstances, a non-linear deterministic process may generate time series that appear to have been generated by a random process. Such processes are termed "chaotic" and have two very interesting characteristics: they are very sensitive to on initial conditions and are unpredictable in the long-term although they usually have a long-term memory (De Grauwe et. a1.1993).

Lately, ideas from the theory of non-linear dynamic systems and chaos theory have been applied in the area of financial markets. The dominance of noise, micro-structures and nonstationarity in financial time series has lead researchers to investigate for low-dimensional semi-chaos (or noisy chaos) rather than for "pure" chaos and to extract the properties of the underlying system, if any. Several studies (Hsieh 1991, Sirlantzis and Siriopoulos 1993, among others) have investigated financial time series for evidence of chaos and long-term dependence, while empirical applications are found in Non-Linear Forecasting (Elms 1994), Chaotic Models (De Grauwe et. al 1993) and Chaos theory-based Portfolio Management (Siriopoulos and Markellos 1995). Recently, it has been proposed (Deboeck 1994, Markellos et. a1.1995) that findings from chaos theory and long-term memory analysis can help in the construction of Artificial Neural Networks (ANN's) for forecasting financial time series.

In this paper we interpret the findings of chaos theory and long-term memory analysis, f or financial time series from the UK., Germany, Belgium, Spain and Greece, in terms of predictability. Based on the above findings, we select the most promising series for successful forecasting - that is the Athens Stock Exchange (ASE) in Greece - and apply neural network modelling in predicting the short-term trend of the General Index of the ASE (GIASE) and the short-term position of a major stock listed on the ASE. The outputs of the neural network for the General Index trend are used in the construction of a trading system. Finally, the performance of the trading system is thoroughly tested against chance and that of passive investment strategies.

The analysis of the study is performed as follows: Section 2 presents a brief description of the methodology used for chaos, range and neural network analysis along with comments on their relation. In section 3, the empirical results of the research are presented and finally, section 4, concludes the paper and offers directions for future research.

2. METHODOLOGY

2.1 Chaos Theory and Long-term Memory Analysis

A typical procedure in chaos analysis (for a review see De Grauwe et. a1. 1993, Deboeck 1994) is to construct a phase space embedding for a time series, and then calculate the dimension of the putative attractor using the Grassberger Procaccia algorithm. A correlation integral is calculated that is the number of points in phase space separated by a distance less than 1, and the power-1aw behaviour of this correlation integral is used to estimate the fractal dimension of the system. The correlation dimension can be interpreted as a lower bound to the significant degrees of freedom of a dynamic system. It is also used to differentiate between low- dimensional deterministic chaos and stochastic systems. If chaos is present the correlation dimension clearly saturates with increasing embedding dimensions of the phase space. If this stabilisation does not occur, the system is considered high-dimensional or stochastic. The time series is correlated when the correlation dimension remains well below the value of the embedding dimension and keeps increasing with increasing embeddings without ever saturating.

The purpose of chaos analysis is to indicate whether strict predictions of the time series are possible, whether these predictions will have a short-term or long-term character, and whether forecasting will be easy or diff icult. The purpose of chaotic analysis is not to make these predictions but to help f ormulate prediction strategies that can be backed by f undamental analysis.

Rescaled Range Analysis - R/S (see Deboeck 1994) can distinguish a random series f rom a non-random series, even if the random series is nonGaussian. R/S analysis is based on the concept that the range of the deviation of a random time series should increase with the square root of time. According to the R/S test, long-term dependence is detected through the Hurst exponent (H) which is connected to the non-periodic cycle length of the series. This cycle is defined as the average period that the long memory of the series dissipates. Long-term dependence in the R/S sense can be described as extended periods of similar overall behaviour that are of unequal duration. The Hurst coefficient H could be interpreted as a measure of the bias or trend in a time series. H equal to 0.5 denotes a random, uncorrelated, independent series. An H different from 0.5 can be interpreted as a bias or memory effect. The strength of the bias depends on how far H is above 0.5.

Whereas chaos analysis addresses the issue of strict predictability of a time series, R/S analysis addresses the issue of formulating long-term or shortterm betting strategies with favourable statistical odds. In cases where data follow a random walk (H=0.5), no successful trading strategies can be formulated. In cases where data follow a biased random walk the results of R/S analysis can be used to develop betting strategies with favourable statistical odds. The presence of long-term dependence or Hurst statistics in financial assets has important implications for many of the paradigms used in modern finance. Optimal consumption/savings and portfolio decisions may become extremely sensitive to the investment horizon. Problems arise in the pricing of derivative securities using martingale methods and traditional tests of the CAPM and APT are no longer valid.

Chaos analysis can indicate the degree of a system's - in our case the stock market - predictability and also give a lower bound to the degrees of freedom that are needed to represent the system. R/S analysis can estimate the randomness and the long-term memory of a series. Series with Hurst exponents different than 0.5 are considered more suitable, than random or close to random time series for pattern recognition modelling. The long-term memory can serve as an upper bound to the number of instances that a model should consider in order to remain in periods of similar statistical behaviour.

2.2. Artificial Neural Network Forecasting

This study sets up two distinct forecasting problems: (a) to predict the short-term trend of the GIASE index, using a small technical analysis information set and (b) to predict the position of the National Bank common stock, in a longer horizon, based on a wide set of variables that includes both technical indicators and fundamental inf ormation. We will refer to the first problem as the trend forecasting problem and the second as the position forecasting problem.

In the trend forecasting problem the defined task is to predict the trend for the following five days of the GIASE index, where trend is the moving average of the next five daily price momentums. Based on the recommendations of a group of technical analysis experts the following price, trend and liquidity indicators for the GIASE were used: the four last price momentums, the MACD(18,9,3) trend indicator, the KAIRI(10) trend indicator and the moving average of the last three trading volumes. First differences were used partly to induce stationarity, and partly to clarify non-linearities by reducing the effects of any short-term linear autocorrelations. Technical analysis transformations of the original prices are used in order to provide noise reduction and obtain a more uniform distribution of data.

In the position forecasting problem the defined task is to predict the percentage change for the National Bank of Greece common stock, 10 days ahead. Seventeen variables were used: the last trading volume of the stock, the last two common stock price returns, the last two preferred stock price returns, a 10-day exponential moving average of prices, the MACD(18,9,3) technical indicator, the P/E ratio, the last dividend amount per common share, the National Bank book value, the last trading volume of the ASE, the last two price returns of a stock relevant to that of the National Bank, the last two price returns of the GIASE index, an inflation index and an industrial production index.

In the construction of a neural network there are three crucial parameters that must be determined: the number of input training patterns, the number of units (nodes) in the hidden layer and the duration of training. The number of training patterns is usually determined empirically while the other two parameters are optimised through a trial and error process. We propose that the number of training patterns should be determined according to the average cycle found by R/S analysis, in order to learn from a homogeneous information set that is sufficiently large to generalise. The units in the hidden node reflect the general key features of the data that must be recognised by the network, and therefore the fractal dimension of the series - as an estimation of the significant variables of the system-can be used for the determination of the number of hidden units. The networks are evaluated according to the Root Mean Square Error Criterion (Rmse). The Determination Coefficient (R2) is used, as a measure of performance, if differences between alternative networks according to the Rmse criterion are small. A sigmoidal transfer function and random initial weights were selected for both problems. Each network tested is trained 10 times using different random weight initialisations in order to ensure that the network has not been trapped in a local minimum.

3. EMPIRICAL RESULTS

3.1 Chaos and R/S Analysis

Table 1 presents a summary of the empirical evidence presented by previous research (Markellos et. al. 1995, Sirlantzis and Siriopoulos 1993) for time series from 5 European stock markets. Consistent with research for other markets it has been found that in general emerging stock markets tend towards determinism and chaos, while mature markets are more efficient and random. Siriopoulos et. a1.1995 and Siriopoulos & Markellos 1995 argue that emerging markets when compared to mature ones, are riskier and more volatile, but they are also more predictable.

The best candidate for modelling, according to the results from chaos and R/S analysis, is the Athens Stock Exchange: it has the lowest fractal dimension along with the highest Hurst statistics. In the next sections we shall attempt to model and forecast data from the ASE by applying ANN's.

Table 1. Chaos and R/S analysis results for European Stock Markets

Market	Sampling	Period	D	H	Memory	Comment
UK	Weekly	1984-94	6.3	0.46	270	random walk
Germany	Daily	1980-94	5.8	0.53	1047	inconclusive
	Weekly		6.4	0.60	985	
Spain	Weekly	1980-94	5.7	0.59	1130	semi-chaotic
Belgium	Weekly	1980-94	4.6	0.59	1455	semi-chaotic
Greece	Daily	1986-94	3.7	0.69	779	semi-chaotic
	Monthly	1980-93	2.3	0.66	760	

3.2 Trend Forecesting Problem

Based on an average cycle of about 780 days for the ASE,1000 vectors of inputs/outputs were used for the trend forecasting problem that correspond to the period October 1990 to September 1994. The first 700 were used for training and the last 300 for testing. Network simulations were made on the EXPO/NN^{TM} softtware (EXPO/NN^{TM} User's Guide, 1995) which uses a modification of the back propagation algorithm, with adaptive learning rate and momentum, that provides accelerated conversion.

Table 2 summarises the results concerning the selection of the optimal network topology for the GIASE trend forecasting problem The problem is best represented by a network with four nodes in the hidden layer that is trained for 2500 iterations. When more nodes are added the network overfits the data and the Rmse in the training and test set move in opposite directions. After 2500 training iterations additional training results in increased Rmse and decreased R2. The results of the time consuming trial and error approach validate those of chaos analysis, since we find that the fractal dimension is a very good estimate for the number of nodes in the hidden layer.

Table 2. Performance of ANN's for different architectures and durations of training

Iterations - 2500					Architecture - 7:4:1				
	In sample		Out of sample			In sample		Out of sample	
Arch.	Rmse	R^2	Rmse	R^2	Iter.	Rmse	R^2	Rmse	R^2
7:2:1	0.0016	0.0437	0.2418	0.0538	1000	0.6546	0.0458	0.3719	0.0384
7:4:1	0.0199	0.0888	0.1545	0.0595	2500	0.0199	0.0888	0.1545	0.0595
7:6:1	0.0008	0.0930	0.4411	0.0437	5000	0.1711	0.1429	0.2849	0.0225

The best network selected for the trend forecasting problem - that is a 7:4:1 network trained for 2500 iterations - was then trained on the randomised and time reversed series. If no structure exists in the original data then the performance of the ANN's is due to overfitting and can be replicated on randomised series. On the other hand, if time is important and irreversible then the performance of the ANN's trained on the reversed series, should decrease. The results presented in Table 3 indicate that structure does exist in the GIASE series, since the Rmse of the networks trained on the randomised data are substantially larger. The performance of training on the randomised series represents average values, since the networks were trained on 10 different randomisations of the series. The performance of the ANN's trained on the time reversed series leads us to presume that the best nets are true dynamic models and that predicting the past when knowing the future is more difficult than the opposite.

Table 3. Rmse of best ANN's on original, randomised and reversed series

Data	In sample	Out of sample
Original	0.0199	0.1545
Randomised	0.1818	
Reversed	0.1646	0.1718

3.3 Position Forecasting Problem

For the position forecasting problem 145 vectors of inputs/outputs were used that correspond to the period January 1990 to May 1991. The first 126 vectors were used for training and the last 19 for testing. Network simulations were made on the Profile ANN Applications™ software package (Profile Neural Applications™ User Guide and Reference Manual, 1995), that uses a standard back-propagation algorithm. By following the same methodology as before it was found that the best net has 6 nodes in the hidden layer. In the test set the Rmse was 3.139 and the R2 0.121. The performance of the network was very good with an accuracy of 68% for a rise/fall prediction for the following 10 days. The time and costs involved with the selection, concentration and analysis of the information set used by this network was substantially higher when compared to the ANN's used previously. Although the performance obtained is very good it is left for future research to decide if the performance by ANN's trained on wide information sets justifies the increased time and cost.

3.4 Trading the GIASE index

This section discusses the process of translating ANN outputs, for the GIASE index trend forecasting problem, into trading orders and the measurement of realised profitability. The trading rule is extracted by optimising a mathematical formula of ANN outputs in the training sample. A simple rule that was found to be effective was: buy (sell) when the ANN output is positive and larger (smaller) than yesterday's output. An optional filter rule allows to sell only if at least four days have passed since the last buy.

The trading rule was applied in the test sample ANN outputs and the results of trading are shown in Table 4. The trading system performed excellently, producing returns much higher than passive buy and hold strategies. The inclusion of the filter rule resulted in higher returns and less frequent trading. The system managed to realise and exploit half of the ideal or maximum potential return of profit opportunities.

Table 4. Performance of the ANN trading system

Days Buy & hold return Max potential return	300 4.05% 94.5%	
	FILTER	NO FILTER
Trades	11	45
Win/loss	10/1	28/17
Total return	47.6%	36.1%
Standard deviation	0.03719	0.02109
Residual test Z-score	3.53	2.26
Model efficiency	50.4%	38.2%
Max gain	12.42%	5.69%
Max loss	-1.08%	-5.3%
Sharpe ratio	8.23	9.06

Performance could be further increased if the trading capital was invested in the money market, when not invested in the stock market. Thus, the trading system performance could reach 60%, since the system stays in the stock market only 25% of the time (80 days). The significance of the trading system returns is further reinforced and statistically tested through the rather extreme "profit residual test". The question is: did the system outperform the naive strategy by an amount sufficient to conclude that the difference was not solely due to random chance ?

The residual profit (R_r) is defined as the difference between the system's profit and the average per-trade-profit produced by a buy and hold strategy; it represents the portion of the trading system that cannot be explained by the long-run trend of the market. R_r is tested in order to determine if it is significantly different from zero. As shown in Table 4, the "profit residual test" z-scores are highly significant at a 99% level for the ANN trading system returns.

4. CONCLUSIONS

The objective of this study was to utilise the findings of chaos theory and R/S analysis in the construction of ANN models and trading systems. We found that among the mature markets of Germany and UK and the emerging markets of Belgium, Spain and Greece, the Greek Stock Market - as realised in the prices of the GIASE index - was the best candidate for ANN modelling. The empirical evidence showed that the ASE is a low-dimensional semi-chaotic system, with Hurst statistics and a significant long-term memory of about 3 years. Two ANN distinct models with different tasks, constructed in in accordance with the indications of chaos and R/S analysis and trained by different simulation shells and on different information sets, were found to give very good representations of the data. The ANN outputs of the first model were used in the construction of an active trading system. This system was found to perform excellently in terms of return, frequency of trading, risk and statistical significance.

It must be noted that the techniques discussed in this study are phenomenological in that they attempt to assess the qualitative character of the stock market dynamics - and to make predictions based on that understanding without attempting to provide an understanding of the mechanisms that ultimately govern the behaviour of the system. Deterministic chaos theory and ANN forecasting are closely related since predictioh is, after all, the sine qua non of determinism.

Future research will concentrate on ANN modelling in the phase space, data space and frequency domain and in filtering out noise from financial time series through unsupervised networks.

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