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MODELING CHAOTIC BEHAVIOURS IN FINANCIAL MARKETS

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Abstract

Lack of deep trading volume, increasing levels of hot money and information, flexibilities of hedge funds and volatilities in emerging markets interrupt the linear relationship between risk and return. Due to corrupted risk perspectives and irrational risk appettites of the market participants, chaotic patterns and non-linear behaviours in financial time series might occur in emerging markets.

Traditional econometric models are not able to capture chaotic nature of the markets due to their strick assumptions on time series such as requirement of normal distribution for the series. Recently, artificial neural networks, wavelets, fuzzy logic and genetic algortihms have been used to model chaotic behaviours. This paper discusses the reasons of emergence of chaotic patterns and algorithms of modeling of those patterns. Neural networks and wavelets are introduced as modeling methods with a simple simulation based on feedforward neural networks. The paper concludes that successfully designed hybrid intelligent models might capture the chaos and non-linearities in the markets.

Key Words: *Chaotic markets, Nonlinear dynamics, Neural networks, Wavelets*
JEL classification: C45, G12, G15.

1. Introduction

It is argued that intensive and fast both money and data flows help financial markets to be more efficient. However, recent research display the fact that globalization of capital and information has inverse effects on the efficient allocation of capitals and market efficiency. The complex structures of markets and behaviours of market participants make financial markets less predictable. Therefore, conventional econometric models have become insufficient to capture complex and chaotic nature of the markets.

Nonlinear dynamics has become a crucial research area with participants from economics, econometrics, physics, mathematics and psychology. With nonlinear dynamics, deterministic processes might generate chaotic and cyclical behaviours.

In finance, capturing chaotic and non-linear behaviours in returns is very difficult by employing conventional econometric models. Especially the markets in which aims of traders vary according to their risk perceptions and appetites, -i.e. exchange rate markets and stock markets-, face with non-linear patterns in returns.

The issue related to usage of linear statistical models is highlighted by their lack of modeling capacity in predicting future behaviours in basic financial variables due to their assumptions on normal disptibution and linearity between risk and return. Non-linear models are able to capture irregular financial behaviours. Nonlinear models are applied on a number of areas in financial markets, banking, economic growth and business cycles.

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In terms of finance theory, hypothesis of efficient markets have been in question since the linear models are not able to capture chaotic behaviours. The hypothesis argues that any available information is immediately reflected in the price of financial instruments. However, since linear econometric models do not capture the non-linear behaviours inb returns, it seems that market can not be predicted.

New computer based technologies such as neural networks, genetic algorithms, decision trees and wavelets have created a new ideology offered in the theory of dynamic systems. The aim of this paper is to discuss modeling chaotic behaviours in financial markets with stochastic, non-linear dynamics models such as neural networks, genetic algortithms and wavelets. Chaotic models provide close approximation for the financial data series which shows how important it is to explore the behaviour of returns as non-linear dynamic systems.

In the next part, chaos in financial markets is discussed. Some descriptions of chaos in terms of finance are introduced, as well. In the third part, a general outline for modeling chaotic behaviours in financial markets is constructed. Different methodologies for capturing chaotic patterns are compared and some combined non-linear models are discuused. As an application, Istanbul Stock Exchange National 100 Index is modeled with feed-forward neural networks in a basic framework. Some other applications in the literature are mentioned as well. The paper ends with suggestions for future research.

2. Chaos and Financial Markets

Chaos is any order confusing the minds. It is an infinite number of unstable periodic cycles of increasing periodicities. In mathematics, chaos is a bounded deterministic system with a positive Lyapunov exponent. In finance, it is complex nature of the markets arising from rapid and unsymetric information flows resulting in non-linearities in returns. In the financial time series, the error times propagates in unpredictable ways which leads modeling impossible.

To capture this nature non-linear and intelligent models are used to control nonlinear dynamics. Certian control methods have been emerged in finacial econometrics. Methods based on past data have statistical problems in terms of distribution and serial correlation. Neural nets and wavelet nets, on the other hand, do not require such kinds of asumptions which make them more usable in chaotic markets. Feed-forward neural networks, for example, control that mechanism with time delays entraining chaotic patterns in the data.

In a chaotic dynamical systems, there should be a large, unstable and complex set of initial conditions. According to Lyapunov exponent, the predictability horizon increases merely logarithmically with the precision of assesment. For example, an increase in precision by a factor of ten, the prediction rises two more time units.

However, it should be kept in mind that in the long-run chaotic patterns are not easy to capture. While in the short-term non-linear behaviours might be modeled by chaotic methods, in the lon-run it is nondetermistic. In other words, chaos is not a complete disorder. Chaos is disorder in a deterministic dynamic environment which might be detected for short-term analysis.

According to Stein (1999), stochastic non-linear models create chaotic dynamics because of heterogenious expectations of market participants. Since non-linear chaotic models have no autocorelations in returns which make them outperform than conditional econometric models. Antoniou and Vorlow (2003) argue that underlying dynamics of stock return sequences are characterised by strong aperiodic cyclical behaviour. That conclusion indicates a complex-deterministic component in the dynamical underlying process.

Recent literature show that efficient market hypothesis is not valid in finnacial markets due to its strick assumptions on the markets ans statistics. Markets are complex, chaotic, time-scaled dynamical systems. For example, neural networks have advantages in capturing those dynamic over conventional econometric methods. They analyze chaotic patterns rapidly with accurance.

Due to the fact that they do not make any assumptions about the nature of the distribution of the financial time series, neural nets do not create bias, as well. It is expected that more accurate prediction results can be optained with artificial methods if the relationship among the inputs does not fit an assumed model. Papadourakis, Spanoudakis and Gotsias (1993) state that this result is expected because of short period of the theory and information technologies. Market applications are often one step removed from the decision making process.

There are alternative or combined artificial models used to capture chaotic behaviours in the financial markets at accurate levels. The set of models starts with artificial neural networks. Fuzzy networks and genetic algorithms have followed neural networks. Recently, wavelets are employed to time-scale financial analysis and a combination of the neural networks and wavelets, namely wavelet networks promise accuracy in modeling financial markets. The next part of the article discusses the alternative methodologies for predicting financial markets and variables.

4. Modeling Chaotic Behaviours in Financial Markets

Markets are complex feedback systems in which participants may overreact to information. Linear risk-return relationship in returns might be damaged due to complex nature of the markets, transaction costs, thin trading and high volatility. Feedback mechanisms imitate the dynamics of nonlinear systems since they have non-proportional relationship between risk and return. Non-linear behaviours in returns suggest that efficient market hypothesis is in question. Non-linear dependencies in returns of financial instruments highlight chaotic patterns.

The efficient market hypothesis is related to the rational expectations theory which states that market participnats aims at maximising expected returns from their investments with their risk appetite. However, the theory is contradicted by empirical results. Market participants should deal with transaction costs, different information sets and different time scales. Therefore, the expectations are heterogenious and should be priced in non-linear and complex methodologies.

Neural networks, fuzzy logic and wavelets are most commonly used methodologies in modeling chaotic behaviours in financial markets. Artificial neural networks are easily constructed computer based models. They are inspired by examining the human brain. Architecture of artificial neural networks imitate biological function. They can be seen as pattern classifiers. The information coming from input variables flows within the hidden layers in the network and is tarined with weighted connections. They have tolerance to noisy time series.

A network has inputs, hidden and an output layers. In general, a neural network is constructed with multi-layer neurons which are connected to each other. The input layers are the dependent variables or factors in the system. The inputs are passed to medium processing units labelled as hidden layers. The inputs are multiplied by a weight (w_k) selected randomly, and results are transformed to the other layers with a non-linear transfer function. The hidden layers processes the input factors and passes the signals produced in the output layer. The process is repeated until the the output reaches at desired level with an acceptable accuracy.

Figure 1. A multi-layer neural network architecture[1]

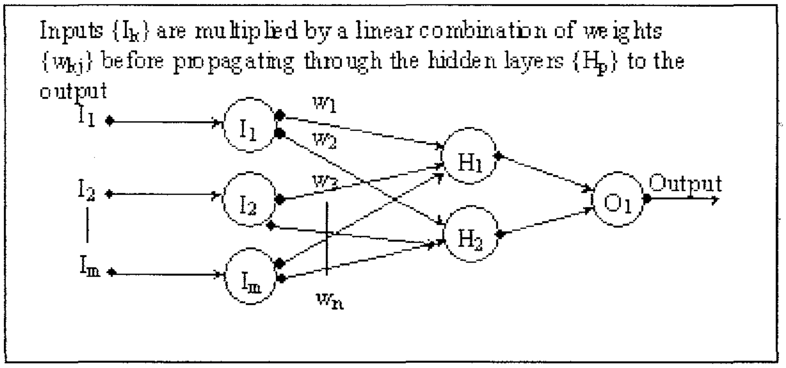


Figure I

An activation function, which may be linear or non-linear, maps input into a bounded range, i.e. [0, 1] or [-1, 1]. There are certain types of activation function, namely, hyperbolic tangent, logistic, threshold, gaussian or sigmoid. According to Klimasauskas (1993) the sigmoid function works best when learning about average behavior, while the hyperbolic tangent function works best when learning deviation from the average. In that framework, a single unit adaptive network with two binary inputs has the output below:

$1 \text{ if } W_0 * I_0 + W_1 * I_1 + W_b > 0$
$0 \text{ if } W_0 * I_0 + W_1 * I_1 + W_b <= 0$

The networks is expected to learn the following pattern: output a 1 if either I_0 or I_1 is 1. By changing the weight by an amount proportional to the difference between the desired output and the actual output, the network is adapted. The process is called as perceptron learning rule and can be denoted as follows:

$$\Delta W_i = \Omega * (DO\text{-}AO).I_i$$

where Ω is the learning rate, DO is the desired output, and AO is the actual output.

In conventional econometric methods, such as Auto Regressive Moving Average, regression rules are strictly defined. Mathematical formulas define the dynamics of modeling. Artificial neural networks, on the other hand, do not perform according to predefined rules. In that respect, neural networks have the ability to learn from input data and produce an accurate output for previously unseen input data even if time series of inputs contain missing data.

As an alternative for neural networks, wavelets are developed in producing signals. According to wavelets, fixed time scales are not adequate for capturing the perception of risk and return. Wavelets assess risk at different time scales and the pass volatility from one scale to the other. Breymann et al. (2000) display long-term correlations from large to small time scales in return volatility. The wavelets capture volatility at different sampling rates are introduced by Gencay and Selcuk (2004). According to the model, wavelets captures the

[1] Sheikh, S., Understanding and Implementing Neural Networks, Neuropsychology and Instructional Design, 2005

non-linearities at a variety of sampling rates simultaneously. According to Gencay and Selcuk (2004) by assuming that N is the longest dyadic piece of the series, multiresolution analysis should be performed down to level J, which is equal to $\log^2$ (N) on the squared return series. An additive decomposition is reached by the j-th level wavelet detail Dj associated with changes at scale $\lambda j (j = 1, ..., J)$.

Ramsey (2000) lists five frameworks in which wavelets are used; namely, i) exploratory analysis, ii) density estimation and local inhomogeneity, iii) wavelets estimators, iv) time scale decomposition, v) forecasting. As a signaling process, a wavelet has genders, father wavelets ϕ and mother wavelets ψ. The father wavelet integrates to 1 and the mother wavelet integrates to 0. The father wavelet represents the low-frequency part of the signal while the mother wavelet does high frequency part.

Recently, a combination of neural networks and wavelets has been used to construct an intelligent architecture system. For example, a discrete wavelet transform allows researchers to reduce the training time of the neural network. Shin and Han (2000) develop an integration model of joint time frequency filtering methods and neural networks. They have two kinds of integration approach; i) single recurrent neural network model combined with the filtering methods, ii) multiple recurrent neural network models combined with the filtering methods.

It is possible to design alternative combined models with intelligent computer based systems. The models vary on the capacities of the information systems used and "random" dream power of the researchers. The next part is introduced some basic applications of neural networks in finance.

5. Applications of Chaotic Models in Finance

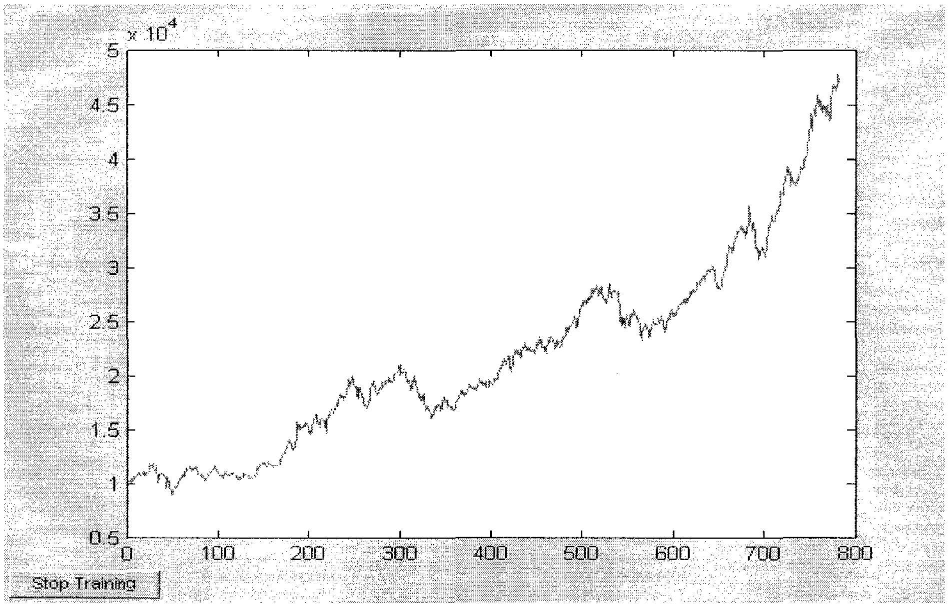
Zahedi (1993) focuses on the fact that intelligent systems contain unique qualitative methods for business that traditional methods in econometrics might not offer because of complexity of their mathematical functions.

Intelligent systems can be used in finance as following goals:

- forecasting of financial and economic time series
- credit approval
- project management
- credit default modeling
- ratings of risk factors
- detection of "error terms" in the financial data
- predicting investors' behaviours
- constructing optimal capital structure

In finance literature, intelligent systems are generally used to model market risk factors such as exchange rates, interest rates and stock prices. Though modeling of market risk factors is out of the scope of this paper, it might be useful to show an example for financial time series prediction. In following graph, a simulation based on feedforward neural networks is presented. The simulation uses daily closing values of Istanbul Stock Exchange National 100 Index from 01.01.2002 to 01.02.2006 and tries to model the index. The time series of the index is trained and compared to the actual closing prices of the index. As it can be seen in the graph, the trained artificial algorithma and the actual index move in paralel direction successfully. Although it is just a simple example, such kinds of models can be improved by combining econometric or other intelligent models like wavelets.

Graph 1. A Comparison of Trained and Actual Indexes of ISE-100



6. Suggestions For Future Research

With incerasing levels of money and information flows, financial markets have had more complex natures. In those conditions, detecting chaotic and non-linear behaviours in financial markets is difficult by using merely traditional. econometric methods. Though efficient market hypothesis states that market players try to maximize expected returns from their investments with their risk appetite, it is not easy to model risk and return relationship and reach an accurate desicion making process with traditional analysis methods.

Due to their lack of modeling capacity in predicting future behaviours in basic financial variables, traditional statistics are not successful in capturing chaotic behaviours of the markets. Since traditional methods have certain assumptions like normal disptibution and linearity between risk and return, they can not detect the non-linearities in the returns of financial variables. On the other hand, non-linear models might capture irregular financial behaviours since they have more flexible assumptions.

In finace and economics, certain artificial methods are succesfuly used to model financial variables such as neural networks, wavelets and wavelet networks as a hybrid model. However, it should be kept in mind that they are accurate in short-run due to their nature of training algorithms. In the long-run, they are not able to capture chaotic patterns since in the long-run economic fundamentals rather than past historical values used to train the intelligent systems have affect the future values of the financial and macroeconomic variables.

Intelligent systems need time and support from information technologies to recover their shortages. Though they are labelled as "black boxes" in the literature, they present a revolutionary perspective for modeling financial variables. Combination of traditional and intelligent systems and more complex hybrid systems, -i.e.wavelet networks- might be useful to recover the deficits of artificial modeling methods.

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