OPTIMAL INVESTMENT POLICIES AND OSCILLATORS OF STOCKMARKET TECHNICAL ANALYSIS. APPLICATION IN THE IMPACT OF THE WAR IN YUGOSLAVIA TO THE GREEK STOCKMARKET.

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Abstract

In this paper we analyze some price oscillators of Stockmarket technical analysis as linear digital convolution filters. We review some of the theoretical published research on optimal trading policies in stockmarkets and we give an application of this approach in the negative shock impact of the war in Yugoslavia to the Greek Stockmarket.

Key words: Portfolio Selection, technical analysis, stochastic optimal control, digital linear filters, time series. JEL C3, C4, C5

1.Introduction

In this paper we shall not investigate all the negative impacts of the war and bombing in Yugoslavia, to the Greek Domestic Economy, but we shall take the opportunity, to study only the shock-waves to the Athens stock exchange market.

The problem of profitable and optimal trading in Stockmarkets is the major choice which investors are facing daily. On the other hand, such decisions are also models of investment decision in other areas of Finance and Economics. The solutions that are discovered for Stockmarkets are often formally the same with solutions in the Microeconomics of firms or even of policies in Macroeconomics of the Government. Academic research has considered the subject of much worth for investigation and since 1967 till today, many papers, from famous economists, has been published about it. It was soon understood that even relatively simple and common problems that are decided empirically are far from simple in their full theoretical formulation. Any one that has attempted to apply any of the theoretical solutions in real situations of Stockmarkets has realized that academic publications have very general and not easily applicable abstractions. An example is the utility function. At the same time they put very restrictive assumptions about the movement of prices, that are rarely met with such simple symmetry, in reality. A question is early put: “Is academic research supporting the empirical trading rules of technical analysis?” There are strong opponents of the concepts of the academic research, among the technical analysts and
investors, that would reverse the question to: «Does reality of Stockmarkets supports the results of academic published research?» It is to admit nevertheless that some of the results of academic research make use of very sophisticated formulations, like the stochastic differential equations, stochastic optimal control, Bellman’s maximum principle etc., with which is familiar only a small minority of the investors. The question of course remains if the above results are enlightening and applicable even for the few that have familiarity with all the involved formulations. The author’s experience is that the academic publications are often much too complicated for direct applications. They are nevertheless encouraging. Any serious application must involve computer experiments and numerical specification of parameters for particular Stockmarkets, that bridge the gap of theoretical concepts and practical results. Academic research seems to be interested to describe the behavior of investors and for this they introduce the utility functions of the profits, which is not determined and is assumed to summarize the subjective or irrational behavior of the investors. If this function is eliminated many of the published results became trivial for trading applications. On the other hand there are some important exceptions to this and furthermore the theoretical formulation, even only with an abstract existence of solution, offers much in the confidence of the investor for an appropriate trading system that can bring to him profits with a consistent, best possible and rationally explained method.

In this paper we analyze explain popular price oscillators like the PrOsc (5-70/50) and RSI, by abandoning the «null-oscillations» assumption, and by considering oscillators as discrete filters that extract oscillations of the regression path. We give also a stochastic differential equation formulation, in ITO’s calculus, of the concept of oscillations. We give a formulation of the Eliot’s wave theory. Finally we apply a discrete time version to study the impact of the war in Yugoslavia to the Greek Stockmarket. An almost clear oscillation appears and a lowering of the momentum of the growth trend.

2. A short review of some of the published academic research findings.

The first papers to formulate and solve the problem of optimal portfolio selection and trading, were two papers by Samuelson and Merton in the same volume of Rev. of Econ. Stat. in 1968 (see SAMUELSON P.A. (1968), MERTON R.C (1968)) Samuelson solved it in discrete time and Merton in continuous time. The later became known in the bibliography from then on as the «Merton problem». In discrete time the solution was obtained using dynamic programming of Bellman and in continuous time by using stochastic differential equations and ITO’s calculus. Both authors, nevertheless, assumed the possibility of costless transactions, thus portfolio adjustments could be as often as one would like. Both authors solved it under the generality of a utility function of profit and assuming that there was consumption at every time step of a part of the investment, by the investor. The criterion of optimality was the maximization of the total consumption in infinite horizon. Although the costless transaction assumption was not realistic the reader got the idea of the general form of an optimal trading tactic. The solution was among two alternative assets, a risky stock and a riskless bank deposit or bond. The optimal trading strategy that switches between these two alternatives was synonymous with the problem of optimal portfolio selection, as the portfolio was only these two alternatives. There was not given any solution for more than two assets and the stock was assumed to have
constant (exponential) trend. The latter was an oversimplifying assumption, as we mentioned in the introduction, from which nevertheless almost all later advancements did not deviate. This assumption that apart from the (exponential) trend the residual of the process is white noise (or random walk for discrete time) is called in the bibliography «the null» assumption. Almost all later solutions, focused on infinite horizon, were the existence of a stationary optimal policy was easy and possible to obtain. Many years passed till the first publication of the solution of the same problem in continuous time but with transaction costs (see CONSTANTINIDES G.M. (1979), MAGILL M.J.P.-CONSTANTINIDES G.M. (1976)). The papers by Constantinides G.M. were pioneering and ahead of their time. They tried to solve problems that required techniques of stochastic differential equations that were known only to a very small minority of experts in the field and they were not economists. Later an elegant and rigorous solution to the same problem was published by Davis M.H. and Norman A. R. (see DAVIS M.H.-NORMAN A.R. (1990)). The transaction costs are assumed to be a fixed percentage of the amount in the transaction. The same problem was solved again under more general forms of the transaction costs like convex and quadratic functions. The solution was still for two only assets. For the first time appeared in the publications the concept of «optimal buffer-region» or «optimal brake-region». The optimal portfolio was not adjusted to changes of the stock prices, because of the transaction costs until the first time deviation drives the previously determined optimal portfolio outside an «optimal buffer-region» or «optimal brake-region». An other author (see DUFFIE D.-SUN T. (1990)) solved the same problem but under the additional assumption that each time a withdrawal (consumption) or portfolio adjustment transaction is taking place there is, except of the percentage transaction costs also a fixed cost as transaction cost or management fees. This assumption, which is very realistic as each time a trading offer is put in the computers a small constant cost occurs, turns surprisingly the continuous time problem to a discrete one. It is proved that the optimal policy requires transactions at constant time intervals! The situation seems to be similar to the optimal time of ordering in inventory control. Other authors (see DUMAS B.-LUCIANO EL. (1991), TASKAR M.-KLASS M.J.-ASSAF. D. (1988)) solved the same problem as Davis and Norman, but without assuming consumption. They required maximization is of the average value of the final (in the infinite) utility of the wealth. A still later publication (see BROER D.P.-JANSEN W.J. (1998)) solved finally the same problem but for more than two assets so that the term «optimal portfolio selection policy» took its really literal meaning. The solution proved that the optimal portfolio was not at all in general «mean-and-variance efficient»! This was surprising for many authors as almost all of the bibliography in the theory of Portfolio Selection adapted the approach of «mean-and-variance efficient» portfolios (see ELTON E.J.-GRUBER M.J. (1991). An approach by far more risk averse and different from all the previous is to take the optimality criterion to be not the maximization of the average value of a utility but of the probability to succeed profits above a level, or of the speed to succeed profits above some level. (See ROY S. (1995), HEATH D.-OREY S.-PESTIEN V.-SUDDERTH W. (1987), PESTIEN V.C.-SUDDERTH W.D. (1985) SUDDERTH W.D.-WEERASINGHE AN (1989), BREIMAN L. (1961)) There have been
published results both in discrete and continuous time and finite and infinite horizon. In continuous time and infinite horizon the results are easier to obtain.

This approach is related to the slogan «safety first». It is certainly by far more valuable for applications as it avoids the abstract utility function for all time steps. It may be relevant nevertheless to sequentially utility approaches that have a separate utility function for each step (see PHELPS E. (1962), SVENSSON L.E.O. (1989)).

At a first glance it seems that the continuous time assumption complicates the process of solution. We know much more about time series than stochastic differential equations. We know how to handle only a few small classes of stochastic differential equations that are Gaussian processes. In addition the formulation for infinite horizon may seem that complicates the solutions. But both assumptions have as net result a crucial simplification of the optimal solution! It is like the law of large numbers in statistical kinetic theory of gasses that has in the average much simpler equations (the equations of fluid dynamics) than the exact statistical equations. In particular for finite horizon and discrete time, in many cases of utilities it would be not possible to find any optimal solution, which is stationary. But even for infinite horizon the discrete time counterpart of many of the solved cases in DAVIS M.H.-NORMAN A.R. (1990) have not yet been solved in spite the attempts (see ROY S. (1995). In this paper only some qualitative results are obtained. e.g. the existence of a stationary solution, while in continuous time the same problem has been solved!)

No doubt, the problem of optimal portfolio selection and optimal trading is separate from the problem of (optimal) forecasting. Any model of price movements could be used and in the above publications was taken the simplest possible. In other words of constant exponential trend as in the Black-Scholes model.

There are also papers that try to avoid any stochastic assumption for the prices and they simply define optimality of the trading tactic according to profits maximization when there is a suggested trading position for the next day according to neural networks techniques. (See GENCAY R. (1998)). Such papers concentrate on the forecasting problem and try to approach it in a way as realistic as possible.

Neural network techniques give new algorithms of time series forecasting by letting the neural network to learn from past successes or failures. Extended research on data for 10 years in Stockmarkets as published in the latter paper, proves that the universal limit of forecasting the next day (even with the best time series forecasting algorithms as are considered the neural network techniques) is 60%. That is 60% of the next day forecasting (for the prices going up or down) are successful!

There are also other approaches to the forecasting problem based on wavelets and non-linear models of time series (see ZUOHONG PAN-XIAODI WANG (1998)).

3. The price oscillators of technical analysis as digital linear filters and their frequency response.

The main objective in this paragraph is to introduce the use of spectral analysis. We may use it to pickup qualitatively or quantitatively the frequencies of the oscillations of the prices and then apply the more familiar moving average indicators at the right time scale. In order to understand better the concepts and techniques appropriate books of Fourier and spectral analysis should be read. We apply in this paragraph spectral analysis also so as to analyse the standard indicators as filters that cut some frequencies and let other frequencies pass. In this way we may understand what we may expect from an indicator in advance, and we may compare them in a unified way.
In addition, the frequency response of an indicator, shows if this indicator filters a particular frequency from the others, or in other words if its designed to forecast waves or oscillations of a particular period.

A moving average oscillator, denoted usually by PrOsc (n-m/k) is defined as follows:

a) First we take the average value of the last m stock’s price values q (m)
b) Then again the average value of the last n stock’s price values q (n)
c) Then we take the average value q (k) of the last k values of q (m)-q (n)

The oscillator is defined by the «crossing the lines rule» of the curves q (k) and q (m)-q (n). The “crossing of lines rule” sais that a buying signal is given each time the curve q (m)-q (n) crosses the curve q (k) from lower to higher and a selling signal each time the crossing is from higher to lower.

The q (k) is a linear function (in fact a convex combination or weighted average) of the stock’s last n+m+k prices.

\[ q(k) = p(n)c(1) + \ldots + p(n-(n+m+k))c(n+m+k) \]  
with \[ c(1)+\ldots+c(n+m+k)=1 \]

Therefore it is identified as linear (digital) convolution filter of the time series (see KOOPMANS LAMBERT H. (1995) Chapter 4, 6). It has a finite number of weights. Its frequency response is defined as the action of the filter on a base of functions, which is the harmonic (trigonometric) oscillations. As by Fourier analysis any finite sequence can be written as a linear combination of the sine and cosine oscillations, and the filter is linear, knowing the filter is equivalent to knowing how it filters the sine and cosine oscillations at all frequencies. Let a linear filter denoted by L. It can be proved that the filtering of any harmonic oscillation exp(iat) (written in complex exponential form) is simply multiplication by a complex constant:

\[ L(\exp(iat)) = B(a) \exp(iat) \]  

The complex function B(a) is called the transfer function of the linear filter L.

For detailed definitions and proofs of the properties of the transfer function see KOOPMANS LAMBERT H. (1995) Chapter 4 PP 82-83. In particular the simple moving average filter of backward horizon of k steps has frequency response:

\[ B(a) = \exp(-ia(k-1)/2)\sin(ak/2)/k\sin(a/2), \quad -\pi < a < \pi \]  
(see again KOOPMANS LAMBERT H. (1995) Chapter 6 EXAMPLE 6.2 P 171.)

From this it is not difficult to derive the frequency response of the PrOsc filter. Subtracting two linear filters has as transfer function the subtraction of their transfer functions while composition of them has as frequency response the multiplication of their frequency response.

As it is reported in DIMOPOULOS D (1998), research on data of the Greek Stockmarket proved that the most profitable results by trading with such price oscillators and the «crossing of lines rule” are obtained with the PrOsc(5-70/50).

The frequency response of this price oscillator is:

\[ B(a) = (\exp(-ia2)(\sin(2.5a)/5\sin(a/2) - \exp(-35a)\sin(35a)/70\sin(a/2))(1 - \exp(-25a)\sin(25a)/50\sin(a/2)) \]  
(5)

Its absolute value multiplies determines the effect of the filter on the amplitude of the oscillations and its argument the shift on the phase.

The next is a program in visual basic at excel that computes the norm (gain) of the transfer function of PrOsc(5-70/50) with steps of 0.05 in the frequency domain. The unit of time is one day.
Sub ConvolutionFilterfrequencyresponse()
Dim x As Single
Dim y As Single
Dim h As Integer
x = 0
For h = 1 To 90
x = x + h * (0.05)
y = Sqr(((Cos(2 * x) / 5 * Sin(x / 2)) - (Cos(35 * x) / 70 * Sin(x / 2))) ^ 2 + ((Sin(35 * x)) ^ 2 / 70 * Sin(x / 2) - (Sin(2 * x) * Sin(2.5 * x) / 5 * Sin(x / 2))) ^ 2 + ((1 - Cos(25 * x) / 50 * Sin(x / 2)) ^ 2 + ((Sin(25 * x)) ^ 2 / 50 * Sin(x / 2)) ^ 2)))
Workbooks("prosctf.xls").Worksheets("sheet2").Cells(h, 1).Value = y
Next h
End Sub

The results of the previous computations are shown in the next diagram.

Figure 1 Frequency response of the PrOsc(5-70/50).

The x-axis is the frequency domain with unit of time one day.

4. The simple moving average oscillators and their frequency response.
Except of the two-moving averages oscillator it is also used in technical analysis the simple moving average oscillator. We take again a moving average of $k$ last prices and then the difference of it from the actual price of that the present day, in other words the residual of the filter. From the definition of the frequency response (or transfer function) (see KOOPMANS LAMBERT H. (1995) Chapter 6) we obtain that the frequency response is:

$$B(a)=1-\exp(-ia((k-1)/2)\sin(ak/2)/(ksin(a/2)))$$

(6)

In $-\pi<a<\pi$

For a moving average of 10 days we get the next diagram of the absolute value of the frequency response:
We use again the previous script in visual basic.

**Figure 2 10-days moving average oscillator: Frequency response.**

The x-axis counts steps of length 0.05 in the frequency domain. The unit of time is taken to be one day.

5. **The momentum oscillators of technical analysis as linear filters and their frequency response.**

In technical analysis momentum is defined as the:

\[ D(k) = \text{price} - \text{(price before k days)} \]  

(7)

In terms of the lag operator of time series \( L(x(n)) = x(n-1) \) we may rewrite the k-order momentum \( D(k) \) as

\[ D(k) = 1 - L^k \]  

(8)

We estimate the frequency response of this operator to be:

\[ B(a) = 1 - \exp(-ia) \quad -\pi < a < \pi \]  

(9)

The frequency response of the Lag operator \( L \) is \( \exp(-ia) \)  

(10)

In the next figure we see the frequency response for the momentum of 10 days.
Figure 3
The x-axis is the frequency with time unit one day.

6. The RSI oscillator and the coefficient of variation (relative standard deviation)

There is in technical analysis another price oscillator called relative strength index (RSI) that was introduced by J.W.Wilder and presented in 1978. (see MURPHY J.J. chapter 10 p 295).

It is defined by the equation:

$$RSI_{in\%}=1-\left(\frac{100}{1+\left(\sum\text{daily price units gained only in the upward days during the last k days}\right)/\left(\sum\text{daily price units lost only in the downward days during the last k days}\right)}\right)$$  \hspace{1cm} (11)

Let us denote by $D(x(n))=x(n)-x(n-1)$ then as the “sum of daily price units gained only in the upward days during the last k days”=$\sum D(x(n))$ for $n=n-k$ to $n$, we rewrite it by simplifying the formula and we get an equivalent form. We put $(x(n)-\text{abs}(x(n)))/2$ and $(x(n)+\text{abs}(x(n)))/2$ for the price points gained in the nth down or up days respectively. Then with simplification on the quotients we get the next

$$RSI = \frac{1}{2}\left(1 + \frac{x}{|x|}\right)$$  \hspace{1cm} (12)

We denote by $x$ with bar the average of the signed price points gained in k-days (as are the smoothing days of the RSI) and by absolute value of $x$ with a bar the average price points in absolute value gained in k days.

For normal random variables it holds that

$$|x| = \sigma / \sqrt{\pi}$$  \hspace{1cm} (13)

thus the RSI becomes a simple formula of the coefficient of variation.

$$RSI = \frac{1}{2}\left(1 + \frac{\mu \sqrt{\pi}}{\sigma}\right)$$  \hspace{1cm} (14)

From this we deduce that this oscillator and its success is not accidental but is related to a well known and very useful coefficient in statistics.

7. Elliot’s wave theory.

There is a very attractive old and classical theory of the movement of prices in stockmarkets, known as “Elliot’s wave theory”. A concise description of the theory can be found in MURPHY J.J. chapter 13 pp. 371-413 (see also ELLIOT, R.N. (1980) and FROST, A.J.-PRECHTER R.R.(1978)). This theory has come out from long experience and is mainly an informal and empirical theory. We assess that this theory supports our approach that there are 1st moment oscillations in the time series. We shall give a formulation to some of the ideas of the theory with well-known wave equations that are partial differential equations. The basic tenets of the Elliot Wave theory are three and in the next order of importance: a) pattern b) ratio c) time. The main pattern according to Elliot’s theory is the wave pattern. The basic ratio of importance is the retracement ratio. In other words after an upward movement and a reversal of the trend, what percentage of it is the downward movement. Finally timing according to Elliot is described very often with numerical relations that come from the Fibonacci numbers $(x(n+1)=x(n)+x(n-1), x(1)=1=x(2))$.

A summary of the Elliot’s approach is contained in the next statements:
0) A wave is a monotonic movements after and before two other movements in the opposite direction. (we notice that a more correct term would be monotonic growth impulse rather that wave. Then we could define as wave or oscillation two successive monotonic growth impulses that alternate.)

1) A trend is divided into three waves three longer in the direction of the trend and two shorter in the reverse direction, in total five waves. Opposite direction waves alternate making a zigzag.

2) A trend correction or retracement is divided into three waves. Two longer in the reverse direction of the trend and no shorter in the direction of the trend. Opposite direction waves alternate. (Elliot classifies many variations of the main correction pattern calling them zigzags, flats, triangles, and double and triple threes.)

3) An upward market cycle is composed from eight waves, five up waves making an upward trend then three down waves. Thus it is composed from an upward trend followed by a downward trend correction. Similarly is defined a downward market cycle.

The next figure shows the basic pattern:

**Figure 4** The market cycle wave pattern of Elliot.

4) Waves can be expanded into waves and subdivided into shorter waves. (This principle seems to be the forerunner of the later theory of fractals of Mandelbrot)

5) The number of waves in trends and trend corrections follows the Fibonacci sequence. (We should not fail to notice that the simplicity of the Elliot’s approach that combines waves and simple numbers, met even in patterns of flower shapes, reminds of Pythagorean ideas of patterns for understanding the world)

6) Fibonacci numbers are used to estimate the retracement ratios. The most common retracements are 62%, 50%, and 38%.

7) The theory was originally applied to Stockmarket averages not on individual stocks and it works better in those markets that the largest public is involved and the laws of large numbers hold better.

If we would like to translate Elliot’s concepts of wave, trend and market cycle in to our approach with time series we would make the next correspondence:
trend = the superposition of a trend in the form of monotonic non-periodic regression path (1st moment) of a time series and an oscillation of the regression path during its period plus of course some random innovation.

market cycle = the superposition of an non-periodic trend part of the regression path and two oscillations of the 1st moment at different periods, plus again a random innovation.

The concept of Fibonacci numbers is very close also to the concept of recursive and autoregressive relations, except that it is not applied only in the time domain but also in the frequency domain. The latter is an approach that only relatively recently has been implemented for forecasting in time series through the neural networks and multi-resolution training of them. (see SCHALKOFF R.J. (1997) chapter 6 p146)

8 Wave equations and price oscillations

Strictly speaking a wave in physics is not only an oscillation in time but oscillations distributed in space also such that their phase difference makes at any instant a waveform as the inter-temporal waveform of an oscillator. In Stockmarket prices it is not obvious what magnitude would play the role of space location. A suggestion was given in the paper KYRITSI S C (1999) of the author, that we may define waves of demand and supply that result to oscillations of prices and volume, but this would be a totally new and different study that we not pursuit in this paper.


It is worth formulating price oscillations with real stochastic differential equations.

\[ dp = (b \sin(\omega t + c) + r) \, dt + \sigma dB \]

The discrete time formulation of this model is:

\[ p(n) = (b \sin(n \omega c) + r + \epsilon(n))p(n-1) \]

With \( b \) we denote the amplitude of the price rate \( r \), per time unit, with \( p \) the price at time \( t \), and \( B \) is a Brownian motion. The constant \( \alpha \) gives the frequency of the oscillation, the constant \( c \) the initial phase of the oscillation and the \( \sigma \) the volatility or standard deviation of the rate. This ITO process is a lognormal process. If \( b = 0 \) then the solution of this equation is

\[ p(t) = \exp((r - 0.5 \sigma^2) t + B(t)) \]

An other choice would be to postulate an explicit equation like the next:

\[ p(t) = \exp((r \sin(at + c) - 0.5 \sigma^2) t + B(t)) \]

(22)

In the next paragraph we apply and estimate a normal rather than lognormal discrete time model on real data of the Greek Stockmarket. The innovation and oscillation is on the price and not on the rate. The model has equation

\[ p(n) = a \cdot n + b + c \sin(\omega n + \phi) + \epsilon(n) \]

That is a superposition of a linear trend with an oscillation trend.

10. An application to the impact of the war in Yugoslavia in the Athens Stockmarket.

Application to the data of the last 40 stockmarket days of the general index of the Athens Stockmarket till the end of April with straight-line trend and no retracement phase shift, give for the model the estimated parameters (we apply here the model not of the oscillating rate but of the oscillating prices). The computer solves such models with algorithms of non-linear optimization. As the relevant theorems are only necessary conditions and not sufficient and necessary, the computed optimal fit
depends much on the initial values put by the computer. After experimentation by giving “best fit” initially from graphical observation we estimated the parameters as shown below. The amplitude and period was determined mainly graphically. The average path has equation:

$$p(n) = (-0.598550)n + (3577.854) + 300\sin((6.28/14)*n + (198534.7))$$

(23)

The day parameter n takes value from 80 to 120 and is till the end of April. The reader should be warned nevertheless, that a high goodness of fit of a forecasting model, for a particular short time interval, as the above, is not adequate for a repetitive, trading based on it and for a long time (years). For a model to be used for repetitive trading and for a long time (years), it should be tested that for the goodness of fit at repetitive forecasting does remains high for long times intervals, that must me at least 2 to 5 years, but even better 20-25 years.

The next figure and tables describe the results.

**Figure 5**

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**Convergence achieved after 8 iterations**

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
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<tr>
<td>C(1)</td>
<td>-0.598550</td>
<td>-0.326384</td>
<td>0.7460</td>
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<tr>
<td>C(2)</td>
<td>3577.854</td>
<td>19.29871</td>
<td>0.0000</td>
</tr>
<tr>
<td>C(5)</td>
<td>198534.7</td>
<td>19517.28</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

R-squared    0.480133 Mean dependent var 3514.002
Adjusted R-squared 0.452032 S.D. dependent var 174.9727
S.E. of regression 129.5233 Akaike info criterion 9.799759
Sum squared resid | 620722.1 | Schwarz criterion | 9.926425
Log likelihood | -249.7527 | F-statistic | 17.08603
Durbin-Watson stat | 0.640855 | Prob(F-statistic) | 0.000006

Covariance matrix

<table>
<thead>
<tr>
<th></th>
<th>C(1)</th>
<th>C(2)</th>
<th>C(5)</th>
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<tbody>
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<td>C(1)</td>
<td>3.363131</td>
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<td>C(5)</td>
<td>4.723391</td>
<td>-472.8303</td>
<td>103.4747</td>
</tr>
</tbody>
</table>

Actual | Fitted | Residual |
-------|--------|----------|
3334.86| 3427.10| -92.2389 |
3444.09| 3314.31| 129.781  |
3467.28| 3243.95| 223.327  |
3471.98| 3229.84| 242.144  |
3537.90| 3274.63| 263.270  |
3625.20| 3369.36| 255.845  |
3598.09| 3495.15| 102.940  |
3630.82| 3627.01| 3.81423  |
3660.26| 3738.71| -78.4539 |
3774.29| 3808.05| -33.7632 |
3759.45| 3821.19| -61.7353 |
3637.80| 3775.39| -137.594 |
3471.48| 3679.62| -208.140 |
3548.46| 3552.70| -4.23638 |
3496.31| 3419.62| 76.6919  |
3511.02| 3306.60| 204.422  |
3376.37| 3235.88| 140.489  |
3121.39| 3221.34| -99.9503 |
3303.49| 3265.73| 37.7551  |
3218.06| 3360.16| -142.102 |
3300.20| 3485.82| -185.620 |
3535.66| 3617.73| -82.0667 |
3621.53| 3729.66| -108.134 |
3720.16| 3799.36| -79.2048 |
3732.64| 3812.92| -80.2797 |
3640.94| 3767.53| -126.588 |
3559.32| 3672.05| -112.733 |
3386.09| 3545.27| -159.177 |
3373.62| 3412.14| -38.5183 |
3350.56| 3298.89| 51.6701  |
3281.96| 3227.81| 54.1487  |
3312.88| 3212.85| 100.032  |
3252.09| 3256.84| -4.75230 |
3431.31| 3350.97| 80.3392  |
3549.70| 3476.49| 73.2097  |
From these results we see that the impact of the war of Yugoslavia is an almost perfect oscillation of period 14 days and amplitude 300 units of the general index. Also if we re-estimate the model in earlier days we find that the slope of the trend becomes less as a result of the war. This analysis of the impact of the war is obviously only in short terms and only based on the behavior of the investors in the Stockmarket. A more complete analysis of the economic impact of the war in Yugoslavia should include the effects on the Greek tourism, the chances of cooperation of the Greek industry with Yugoslavia, the changes in the Labor wages in the Greek industry because of emigrant workers, in general changes in the cost of labor in the Greek industry (see also KIOCHOS P. (1993)) and effects on changes of the cost Greek military resources. As any war it has negative impact on capital markets and the Domestic Economy in Greece.

11. Conclusions
We summarize our conclusions:

1) The assumption that after subtracting a constant rate trend from the stock prices the residual is a stationary time series and any oscillations are therefore of the variance (Box-Jenkins and spectral analysis approach or null oscillations assumption) is not seem to be supported from the statistical data and traditional trading techniques of the investors.

2) It seems more probable that except of non-periodic part of the 1st moment (regression path) there is also a periodic or waving part. Upon this it based the trading techniques with oscillators. There can be performed of course statistical tests that they do not reject the stationarity hypothesis but also analysis of variance that does not reject the non-stationarity hypothesis (see also LIMA P.J.F. (1998). The choice of the size of the horizon is crucial. After subtracting also the 1st moment oscillational part of the time series, there might remain in the residual a 2nd moment (variance) oscillational part. Its significance nevertheless for trading based on criteria of average value of profit is by far less important.

3) Econometrics of stockmarkets seem to omit the analysis of price time series with digital filters that extract oscillations of the first moment. A reason is that digital filters were designed and computed initially for signal theory. Nevertheless their mathematics are part of statistics and time series and are very close relatives to the empirical oscillators of technical analysis of stocks and commodities. The effect of the empirical filters of technical analysis depends completely on the frequency response of them.

4) The impact of the war in Yugoslavia to the Athens Stockmarket during March and April 1999 is best approximated with an oscillation of the general index of amplitude about 300 units and period almost 14 days, plus a weakening of the ascending trend. It has of course as any war a negative shock impact on the capital markets. Further analysis, would show of course deeply negative effects of the war for the Greek Economy, not necessarily related to the stock exchange market, but to the Domestic Economy in General.
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