THE IMPACT OF THE CONVERGENCE OF THE GREEK ECONOMY TO EMI IN THE STOCKMARKET: BAYES, NESTED ESTIMATION OF THE STOCK TRENDS

Costas Kyritsis

To cite this version:

Costas Kyritsis. THE IMPACT OF THE CONVERGENCE OF THE GREEK ECONOMY TO EMI IN THE STOCKMARKET: BAYES, NESTED ESTIMATION OF THE STOCK TRENDS. the Journal Archives of Economic History, 1999. hal-01552352

HAL Id: hal-01552352
https://hal.science/hal-01552352
Submitted on 2 Jul 2017

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
THE IMPACT OF THE CONVERGENCE OF THE GREEK ECONOMY TO
EMI IN THE STOCKMARKET: BAYES, NESTED ESTIMATION OF THE
STOCK TRENDS

By Dr. Costas Kyritsis
National Technical University of Athens

1. Introduction
The time when an economy enters the first world economy is a very interesting time.
It is even more interesting if the group of nations where it enters, in this case
European Union, becomes gradually, with respect to some parameters, the strongest
economy in the world.
Although the Greek economy is by far not perfect or advanced, there is the firm
decision to handle its indices, as much as possible, so as to qualify according to the
standards of European Monetary Integration. These standards are set, for the Greek
economy, mainly in the next profile:
a) The Inflation rate less than 1.5%
b) The deficit of the Government less than 0.9% of the Gross National Product
c) The national debt less than 100% of the Gross National Product
d) Growth rate of the Gross National Product at least 4.5%.

2. Macroeconomics factors influencing the prices in the Athens Stockmarket
There is no doubt that the previous standards of EMI make a profile of a mature
economy and also no doubt that a young state like the Greek (less than 2 hundred
years old) has major difficulties in qualifying in the profile of EMI, before 2001. It is
worth trying nevertheless, even only for the benefit of eliminating the continuous
currency devaluation of the national wealth through the exchange rates.
Experience has showed that the basic magnitudes of Macroeconomics that have
significant impact on the changes of prices of stocks in the Stockmarket are:
a) The average rate of deposit in the banks, or the rate of change of the time-value of
money.
b) The exchange rates
c) Mass-media information about other economies and changes of prices in other
Stockmarkets.
The procedures with which the previous factors influence the changes of prices in
Stockmarket is always through the aggregate demand and supply for each stock:
1) Surplus of demand to purchase stocks in the computer waiting lines creates growth
of the price of the stock (Bull-market)
2) Surplus of supply to sell stocks in the computers waiting lines creates falling of the
price of the stock (Bear-market)
The exact equations of how stochastic demand and supply results in to the random
variables of price and volume and their changes, is not an issue to cover in the present
paper. It is not of intractable difficulty to formulate though.
We shall state, nevertheless, the basic equations of competition of demand and supply for each stock. The equations of two populations in competition have been a topic of systematic study. It may not be surprising that such equations have been studied and solved not in the science of Economics but in Ecology. They are a standard topic in an area initiated by Volterra and his equations for populations.

Let us denote by $x(t_n)$ and $y(t_n)$ the average value, at time $t_n$, of the random variable of the volume of orders of the demand to buy and of the volume of orders of the supply to sell a stock. The next equations describe the interplay of demand and supply:

1. $x(t_{n+1}) = x(t_n)(a-bx(t_n)-cy(t_n))$
2. $y(t_{n+1}) = y(t_n)(e-fx(t_n)-gy(t_n))$

The symbols $a, b, c, d, e, f, g$ are constants defining the competition.

Such equations, formulated in continuous time and deterministic mode are the well known equations of competition in Ecology (see e.g. [Maynard S.J] p 59 formula 36). We notice that they are non-linear equations. They have been solved numerically, studied and applied in many situations of populations in competition. The populations involved here are of the investors who want to buy and those who want to sell. The equations describe the effect in demand and supply of the automatic negotiation algorithm in the computers waiting lines. These equations if formulated in continuous time they do not involve oscillations. But when formulated in discrete time and as stochastic processes or time series, they do involve (non-linear) oscillations which is the common experience for anyone that has spent some time in front of a monitor of a Stockmarket company. If we make use of the prey-predator or host-parasitoid, Volterra equations that different from the equations (1), (2) only at a plus sign instead of a minus sign at the coefficient $f$ in (2), then we get larger scale oscillation.

During 1997 there was a major impact on the price growth in the Athens Stockmarket of the size, at year base, close to 50%. It is supposed that it was created by the fall of the deposit rates of the banks (factor $a$) mentioned in this paragraph.

During 1998 there was an even larger impact on the price growth of a size close to 70%. It is supposed that it was created mainly by the currency devaluation in the exchange rates decided by the government in March 1998.

As the latter case was the most dramatic, we shall try to analyze it with a new statistical method.

3. Bayes fractal-like nested estimation of time series

As it is known there is a topic in statistics called Bayes estimators. (See e.g. [MOOD A.-GRAYBAILL A.F.-BOES D.C.] pp 339-351). The main idea is that when we have a parameter in a distribution that we must estimate, we may assume as a meta-level that it is already a random variable with an a priori given distribution. For example if we are estimating a Gaussian (normal) random variable $N(m,s)$ we may assume that we have a double variation and a second stochastic level and that the parameters $m, s$ are already Gaussian (normal) random variables with means $m_m, m_s$ and variances $S_m, S_s$. It is not that we want to make the computations more complicated but that we need to fit a more flexible model to the real situation.

For doubly stochastic time series see [TONG H.] pp 117-118. We shall describe a general method to refine autoregressive time series models, such that at each refinement, it appears higher order variability and higher Bayes order as discussed.
above. For the sake of clarity we shall apply it to the Black-Scholes lognormal model of the prices of stocks. The model is known in stochastic processes and stochastic differential equations as the geometric Brownian motion. (see [OKSENDAL B.] pp 59-61, 198-199 and 223-225 or [KARLIN S.-TAYLOR H.M.] pp 267-269, 357, 363, 385 and [MALLARIS A.G.-BROCK W.A.] pp 220-223. It is a linear SDE of constant coefficients and multiplicative noise or innovation.

Although much popularity is related to this model, it cannot describe but the buy-and-hold situation in the Stockmarket. We may try to vary this model with the idea of Bayes so as to include reversal patterns and price motion with or without resistance. We supplement the idea of Bayes by corresponding to each new stochastic or Bayes level a finer grid of the argument. In this way different models appear to different scale regimes, but still something is repeated thus we follow also the basic idea of self-similarity introduced graphically by Mandelbrot with fractals and multi-fractals. Mandelbrot has applied his idea of self-similar fractals to the Stockmarkets, arguing that much of the oscillating effects of stock prices are not observed in the Black-Scholes model.

There are many new results of qualitative dynamics of dynamic systems under the term chaos. The ideas are not irrelevant but in order to apply them in a professional way to Stockmarkets we require them in stochastic differential equations or time series (see [TONG H.]).

The idea of nested patterns of tides (trend of a year or more), waves (in seasonal horizon) and ripples (day or intra-day oscillations) goes back to the theory of Dow and Elliott in the Technical Analysis of stocks (see [MURPHY J.J.] pp 24-35, 371-414). [MURPHY J.J.] It is also obvious the relevancy of the Elliott wave theory with Spectral Analysis and fast Fourier transformation in time series.

The way to enhance the buy-and-hold model of Black-Scholes is as follows:
1) We define a nested system of grids in the time argument. For example starting with an horizon of a year we partition it to smaller seasonal horizons (e.g. 60 Stockmarket days). We may continue in this way to monthly, weekly and finally daily horizons.
2) For the first one year horizon we perform an ordinary estimation of the Black-Scholes model. It gives the buy-and-hold trend.
3) In the seasonal horizon we increase the Bayes stochastic order. For each season in the one year horizon we estimate a second Bayes order model. The four seasonal models are pasted automatically to a more flexible overall model than the Black-Scholes.
4) We continue to increase the Bayes order by one for each finer horizon, of a month, a week or a day and we estimate a new model for each smaller horizon.

The resulting time series fits pretty well to the real life surprises of the Stockmarket. The method resembles the splines in numerical analysis only that it is not performed on polynomials and the models are not deterministic but stochastic.

A good question is how we increase the Bayes order. A simple method is to consider the constant coefficients of the initial model as varying linearly relative to time. This introduces for estimation new constant parameters. At each finer grid we assume the previous constant parameters as varying linearly and we estimate the new constant parameters.

In the next paragraph we shall perform the method at two only horizons of one year and a seasonal of 60 Stockmarket days.
As we mentioned in the previous paragraph the Black-Scholes model of the prices of stocks is the geometric Brownian motion in other words defined in continuous time by the stochastic differential equation:

\[ dx = rxdt + \sigma xd\zeta. \]  

Where \( x \) is the price of the stock and \( z \) is a Brownian motion.

In this example we implement the discrete time, non-homogeneous time-series version defined by the equation

\[ x_{n+1} = (r + s e_n) x_n \]

We make use of a close relative to it, which is the next time series in explicit form:

\[ x_n = \exp((r_n + s e_n) n) \]

Where \( e_n \) is a normal error or innovation. We do not insist on any stationarity assumption.

We make the assumption that the «noise» or innovation term is additive in the exponent instead of multiplicative and of constant variance, that is, an homoskedasticity assumption that makes the variance of the residual, in the exponent, constant in time.

This simplifies the estimation of the parameters of the time series

The application of the original model of constant coefficients for an one year horizon is straightforward and is very well known. We proceed with the nested Bayes estimation that we described in the previous paragraph. We assume for the four seasonal (3-months) horizons of one year that the model has variable coefficients and that the coefficients vary linearly with respect to time. This introduces new constant coefficients \( a, b \) in (5):

\[ r_n = an + b \]

The exponent becomes now quadratic with respect to time.

\[ x_n = \exp((an + b)n + se_n) \]

More generally we estimate the equation

\[ x_n = \exp((an + b)n + c + se_n) \]

We notice that the equation is almost the normal curve except of a linear term or sign reversal.

To estimate it we take the logarithm of the prices and apply polynomial regression.

The exponent is in general an at most quadratic polynomial. If the coefficient of the quadratic term is negative, we have an instance of an almost Gaussian (normal) curve, which is interpreted as follows:

1) Increase of the prices with an asymptotic upper resistance, which becomes a reversal pattern (first part of the curve)
2) Decrease of the prices with an obvious asymptotic lower resistance at zero, thus practically without resistance (second part of the curve)
If the coefficient of the quadratic term of the exponent is positive then the probable cases are:
3) Increase of the prices very fast (faster than the simple exponential growth) without upper resistance (second part of the curve)
4) Decrease of the prices with lower asymptotic resistance that becomes a reversal pattern (first part of the curve)

Thus the qualitative dynamics of the stock at each time are described by the above four dynamic states
The results of the least squares estimation of this linear model with time variable coefficients are given below.
The estimated model between the dates 10/03/1998 (n=1) and 05/06/1998 (n=60), that is 60 Stockmarket days is
(8) \[ x_n = \exp((-0.00025)n + 0.023223)n + 7.317873 + e_n \]
The maximum of the normal curve occurs in the day \( n = 47 \) that is in 19/05/98.
In this date the model gives a clear selling signal. Of course we cannot trade with the general index. But it would give one if we had applied it for a particular stock. The author scored code in visual basic in Excell in order to analyse the buying and selling signals during the year. The results were quite positive for forecasting. For further analysis of optimal trading see bibliography below from BREIMAN L. 1961 to GENCAY R. 1998.
The variance of the residual and the goodness of fit are given below:
(9) \( S = 8409.733584 \)
(10) \( R = 92.62713729 \)
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.
In figure 2 we have an superimposed form the general index and the estimated “normal” curve for the seasonal horizon of 60 days.
In table 1 they are given the numerical data of the chart. As soon as we have estimated the model by continuing it in a reasonable forward horizon we have an effective forecasting. The forecasting is corrected at best every day so that the buying or selling signals are with minimum time delay.
We have used data of closing daily prices and not intra-day data. The Bayes nested estimation can be extended for shorter horizons and the exponent becomes a polynomial of order higher than the quadratic.
Figure 2
Table 1

<table>
<thead>
<tr>
<th>Date</th>
<th>General Index</th>
<th>Normal Smoothing</th>
<th>Date</th>
<th>General Index</th>
<th>Normal Smoothing</th>
</tr>
</thead>
<tbody>
<tr>
<td>10.03.1998</td>
<td>1542.017</td>
<td>1517.54</td>
<td>24.04.1998</td>
<td>2437.958</td>
<td>2473.98</td>
</tr>
<tr>
<td>11.03.1998</td>
<td>1577.069</td>
<td>1531.26</td>
<td>27.04.1998</td>
<td>2456.469</td>
<td>2300.71</td>
</tr>
<tr>
<td>12.03.1998</td>
<td>1612.116</td>
<td>1543.62</td>
<td>28.04.1998</td>
<td>2473.89</td>
<td>2445.80</td>
</tr>
<tr>
<td>13.03.1998</td>
<td>1647.124</td>
<td>1537.37</td>
<td>29.04.1998</td>
<td>2490.196</td>
<td>2511.56</td>
</tr>
<tr>
<td>16.03.1998</td>
<td>1682.055</td>
<td>1649.69</td>
<td>30.04.1998</td>
<td>2505.364</td>
<td>2621.44</td>
</tr>
<tr>
<td>17.03.1998</td>
<td>1716.873</td>
<td>1737.37</td>
<td>04.05.1998</td>
<td>2519.372</td>
<td>2602.82</td>
</tr>
<tr>
<td>18.03.1998</td>
<td>1751.541</td>
<td>1754.93</td>
<td>05.05.1998</td>
<td>2532.2</td>
<td>2634.54</td>
</tr>
<tr>
<td>19.03.1998</td>
<td>1786.021</td>
<td>1861.73</td>
<td>06.05.1998</td>
<td>2543.827</td>
<td>2582.62</td>
</tr>
<tr>
<td>20.03.1998</td>
<td>1820.275</td>
<td>1919.91</td>
<td>07.05.1998</td>
<td>2554.239</td>
<td>2509.78</td>
</tr>
<tr>
<td>23.03.1998</td>
<td>1854.263</td>
<td>1950.75</td>
<td>08.05.1998</td>
<td>2563.418</td>
<td>2450.16</td>
</tr>
<tr>
<td>24.03.1998</td>
<td>1887.948</td>
<td>1922.86</td>
<td>11.05.1998</td>
<td>2571.351</td>
<td>2358.15</td>
</tr>
<tr>
<td>27.03.1998</td>
<td>1954.248</td>
<td>2063.32</td>
<td>13.05.1998</td>
<td>2583.437</td>
<td>2494.66</td>
</tr>
<tr>
<td>30.03.1998</td>
<td>1986.784</td>
<td>2083.89</td>
<td>14.05.1998</td>
<td>2587.571</td>
<td>2494.70</td>
</tr>
<tr>
<td>31.03.1998</td>
<td>2018.857</td>
<td>2055.80</td>
<td>15.05.1998</td>
<td>2590.423</td>
<td>2469.84</td>
</tr>
<tr>
<td>01.04.1998</td>
<td>2050.429</td>
<td>1988.78</td>
<td>18.05.1998</td>
<td>2591.99</td>
<td>2500.44</td>
</tr>
<tr>
<td>02.04.1998</td>
<td>2081.46</td>
<td>1995.00</td>
<td>19.05.1998</td>
<td>2592.269</td>
<td>2493.70</td>
</tr>
<tr>
<td>03.04.1998</td>
<td>2111.91</td>
<td>2063.50</td>
<td>20.05.1998</td>
<td>2591.259</td>
<td>2547.01</td>
</tr>
<tr>
<td>06.04.1998</td>
<td>2141.741</td>
<td>2135.31</td>
<td>21.05.1998</td>
<td>2589.963</td>
<td>2573.98</td>
</tr>
<tr>
<td>07.04.1998</td>
<td>2170.914</td>
<td>2129.08</td>
<td>22.05.1998</td>
<td>2585.383</td>
<td>2606.48</td>
</tr>
<tr>
<td>08.04.1998</td>
<td>2199.391</td>
<td>2124.76</td>
<td>25.05.1998</td>
<td>2580.525</td>
<td>2669.76</td>
</tr>
<tr>
<td>09.04.1998</td>
<td>2227.134</td>
<td>2157.39</td>
<td>26.05.1998</td>
<td>2574.396</td>
<td>2621.33</td>
</tr>
<tr>
<td>10.04.1998</td>
<td>2254.106</td>
<td>2158.12</td>
<td>27.05.1998</td>
<td>2567.005</td>
<td>2523.03</td>
</tr>
<tr>
<td>13.04.1998</td>
<td>2280.27</td>
<td>2255.81</td>
<td>28.05.1998</td>
<td>2559.364</td>
<td>2549.07</td>
</tr>
<tr>
<td>14.04.1998</td>
<td>2305.593</td>
<td>2266.35</td>
<td>29.05.1998</td>
<td>2548.484</td>
<td>2591.03</td>
</tr>
<tr>
<td>15.04.1998</td>
<td>2330.037</td>
<td>2339.28</td>
<td>01.06.1998</td>
<td>2537.381</td>
<td>2536.09</td>
</tr>
<tr>
<td>16.04.1998</td>
<td>2353.571</td>
<td>2448.55</td>
<td>02.06.1998</td>
<td>2525.071</td>
<td>2551.47</td>
</tr>
<tr>
<td>21.04.1998</td>
<td>2376.161</td>
<td>2627.90</td>
<td>03.06.1998</td>
<td>2511.571</td>
<td>2581.24</td>
</tr>
<tr>
<td>22.04.1998</td>
<td>2397.776</td>
<td>2623.39</td>
<td>04.06.1998</td>
<td>2496.903</td>
<td>2567.21</td>
</tr>
<tr>
<td>23.04.1998</td>
<td>2418.384</td>
<td>2618.65</td>
<td>05.06.1998</td>
<td>2481.086</td>
<td>2562.82</td>
</tr>
</tbody>
</table>

References

[AZARIADIS C.] Intertemporal Macroeconomics Blacwell 1993


[LUTEKEPOHL H.] Introduction to Multiple Time Series Analysis Springer 1993


