"AN EMPIRICAL INVESTIGATION OF THE EFFICIENT MARKET HYPOTHESIS: THE CASE OF THE ATHENS STOCK EXCHANGE"

Christos Alexakis

Department of Economics and Related Studies

University of York

Heslington

York YO1 5DD

England

This thesis is submitted by **Christos Alexakis** for a D.Phil degree in Economics at the University of York, Department of Economics and Related Studies.

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To my parents

Apollon and Souzana

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ABSTRACT

In this study we tried to examine empirically the Efficient Market Hypothesis for the Athens Stock Exchange under the assumption of a constant equilibrium return. Univiriate and Biviriate statistical tests for the weak form of market efficiency, (Box-Jenkins, Spectral analysis, Granger causality tests and cointegration tests) indicated evidence of inefficiency.

In order to examine the Semistrong form of market efficiency we used publickly available information other than price histories. Granger causality, cointegration tests and regression analysis indicated again evidence against the efficient market hypothesis.

The uniform evidence for Stock Market inefficiency in this study is that daily price changes and monthly returns are possitively and significantly serially correlated. This effect is prominent for the Banking sector. Under the assumption of a constant equilibrium return we explained this pattern as a noise trading effect i.e. the Greek market is driven by psychological factors and arbitrary beliefs e.g. some Greek investors see trends in price changes and trade based on this belief. A statistical relationship between trading volume and price changes gave futher evidence for the above explanation.

Finally, we offer reasons why the noise trading effect is strong for the Banking sector of the Athens Stock Exchange.

PREFACE

My purpose in this study is to examine the Efficient Market Hypothesis for the case of the Athens Stock Exchange. The Efficient Market Hypothesis describes a rational market where all relevant available information is reflected very quickly on prices. In an Efficient Market prices should react only to new unanticipated information, and since this is unpredictable by definition price changes must be unpredictable. In an Efficient Market irrational forces like investors psychology are irrelevant. For many years the Efficient Market Hypothesis seemed to describe adequately the price behaviour in the world stock markets. Nevertheless, recent evidence indicates the opposite. The Efficient Market Hypothesis remains an open issue.

I chose for my investigation the Greek Stock Exchange partly because as a Greek I am interested in the Greek economy, but also because the Greek stock market has not been widely investigated and so I think that this study will add a piece of evidence in the research area for market efficiency in the world stock markets.

The investigation of the Efficient Market Hypothesis is an empirical matter; the Efficient Market Hypothesis is also tested with respect to a specific information set. Thus, in my analysis I will investigate statistically how quickly the Greek stock market reacts to specified information sets. Given some information set I will move statistically from low to high frequencies and vice versa in order to explore if the Greek stock Market can be characterised as an Efficient one.

THE HISTORY AND THE RECENT DEVELOPMENTS OF THE EFFICIENT MARKET HYPOTHESIS. A REVIEW OF THE THEORY AND THE EMPIRICAL WORK

Chapter One

1. The History and the Recent Developments of the Efficient Market Hypothesis

Overview

The Stock market is an institution of considerable interest to the public and of importance to economists. The Stock market is dealing with instruments representing claims of ownership to enterprises of industrial, financial and service character. These claims are viewed by their owners as assets which are transformable into money which in turn is offered for their purchase. The worlds stock markets are the places which offer liquidity ability to the owners of the assets and contribute to the continuous and competitive determination of prices. It is of great importance for stock markets to operate efficiently. In a general sense, an Efficient Stock Market is the market in which firms can make production investment decisions and investors can choose among the securities that represent ownership of firms activities.

Nevertheless, a relationship between stock market activity and gambling has been pointed out very often in the Finance literature. It has been pointed out that the gambler speculates by putting up a stake in a game of chance and that an investor in the Stock market acts more or less in the same way.

There is a tendency to look upon speculation as an unwanted economic activity, as if it were separated from the economic behaviour. Economic activities though, are speculative since they are not completely deterministic.

The fact is that we do not live in a deterministic world; there are only degrees of uncertainty. All economic activities are directed into the future, be it moment or year, and they all depend on expectations about the future. Speculators, in one sense, are the people who take these risks voluntary, taken by someone else to high, given their own concrete circumstances with identification of stake, potential loss and profit. According to Hardy (1930), a speculator wishes *"to gain a relative advantage at the expense of the community either by superior knowledge or by superior luck"*. Nobody under any circumstances, acting in any market would want to exclude the pleasant consequences of superior knowledge or luck provided that they are compatible with the law and the accepted moral standards of the community and the individual.

Turning back to stock market efficiency the efficient market hypothesis implies a special kind of efficiency which is Informational Efficiency. The Information Efficiency is the kind of efficiency when prices, under certain assumptions, reflect fully and very quickly, theoretically instantaneously, every piece of information concerning the traded securities.

Thus, the stock prices at time, let us say t, should react only to relevant information relished at time t, say I_t which according the assumptions underlying the Efficient Market Hypothesis is available to everyone. In an Efficient Market past information I_{t-i} has been already reflected on prices and the price at time t should not respond to such information. If the market at time t-i anticipate some information which released at time t, then the market at time t should react only if the information released was better or worse than that anticipated.

The implication of the Efficient Market Hypothesis as Cootner (1964), put it is *"Since there is no reason to believe that information (news) does not come in the market in a random way, price changes as a result of the information (news) should behave in a random way"*. This implication makes it impossible for someone to forecast consistently price changes and profit from these forecasts, and this is the point where the Efficient Market Hypothesis becomes a testable hypothesis.

Speculators who base their trading strategies on luck are not a matter of the efficient market hypothesis. These speculators do not base their trading strategy on any specific information set and they can not be considered as evidence against the Efficient Market Hypothesis.

On the other hand, the efficient market hypothesis is concerned with speculators who profit from superior knowledge. These people acquire knowledge by gathering and processing information relevant to stock prices before other people do and better than other people do. These well informed investors try to make good estimates of future prices in order to *"buy low and sell high"* since this is the name of the stock market "Game", Adam Smith, (1970). If in a Market there are such speculators who can predict consistently future returns based on a data set available to the market and gain from these predictions

i.e., <u>Gains from prediction</u> > <u>Costs of prediction</u>

then their existence can be considered as a serious evidence against the Efficient Market hypothesis.

The theory of the Efficient Markets has a long history and caused a debate between academics and practitioners for many years now. Some studies gave supportive evidence for the Efficient Market Hypothesis and some others, among them the most recent, did not. Some researchers who have discovered price behaviour different from what the Efficient Market Hypothesis implies and proposed alternative theories to explain these deviations. On the top of that debate *Chaos* theory says that price changes are the result of complex non linear dynamic models. At a first glance price changes may look like random, but if someone looks deep in them will be able to find structure because in *Chaos* theory structure and randomness are closely related.

In this chapter I will give a picture of the history of the Efficient Market Theory based on theoretical and empirical work in this area of research which is still considered as open.

1.1 Fundamental and Technical Analysis

Early works on capital markets by Williams, *The theory of investment value* (1938), and Graham & Dodds *Security analysis* (1934), were built on the notion of "intrinsic" or "fundamental" value of securities which equals the discounted cash flow these securities generate; and the belief that actual prices fluctuate around fundamental values. According to the above idea the suggested strategy for someone is to buy when the price of a stock is below its intrinsic value and sell when it is above its intrinsic value in order to realize trading profits when the disparity is eliminated. Thus, fundamental analysts tried, and still do, to perform projections of securities future cash flows. This involved analyzing factors like the demand for the product, possible future development of substitutes, the environment of the firm and the industry even the economy as a whole. In short, all information relevant to future profitability of the firms in question.

Apart from fundamental analysis investors also applied technical analysis by trying for example to identify specific graphical patterns in stock prices. According to this form of technical analysis, when specific graphical patterns exist with shapes like diamonds, double tops, head and shoulders they can be used as a base for profitable trading rules when an investor will buy or sell according to the trend which the above patterns imply, Levy (1971).

1.2 Random Walks

On the other hand, based on a 1900 Ph.D thesis of the French mathematician Luis Bachelier, appeared statistical evidence that stock price changes are unforecastable since they are a cumulated series of propabilistically independent shocks which are identically distributed. It was claimed that stock prices follow the random walk model:

$$P_t=P_{t-1}+u_t \quad \text{or} \quad \Delta P_t=u_t \qquad (1)$$

$$\text{with} \quad E(u_t)=0 \quad Var(u_t)=\sigma^2 \text{ and } Cov(u_t,u_s)=0 \quad t\neq s$$

where P_t is the price of a security and ΔP_t the price change. The idea was supported by statistical work of Working (1960) and others like Moore (1962), Kendal (1953), Granger and Morgerstern (1963), Fama (1965,1970).

The random walk model seemed to contradict the idea of rational security pricing and seemed to imply that stock prices are exempt from the laws of supply and demand that determine other prices. Furthermore, one could say that according to the Random Walk model investments look like a gambling bet since prices look like a casino roulette outcome.

The Fundamentalists attacked the random walkers by putting forth the argument that if profitable opportunities did not exist and investors should not employ fundamental analysts, why then huge amounts of money were still being spend on research and investment advices. Random Walkers reply was that if fundamental analysis worked profitably, why then new entrants in to the business of fundamental analysis compete these gains away as it happens in any other industry.

Apart from the above debate between random walkers and fundamentalists the random walk requirement of probabilistic independence between successive price changes was too restrictive for being embodied in the optimization literature of the economic theory. The random walk model which seemed to describe the price behaviour was purely statistical and an economic theory which the random walk model should confirm was necessary.

1.3 Fair Games and Martingales

A more theoretically appealing model appeared then on the scene and it was the fair game model, Samuelson (1965), of which the random walk can be considered a special case. The fair game model could be linked with simple assumptions about preferences and returns and not be as theoretically restrictive as the random walk model. According to the fair game model a stochastic process with respect to an information set It, is a fair game if it has the property:

$$E(X_{t+1}/I_t)=0 \qquad (1)$$

Under the assumption of a zero interest rate the fair game model implies that in an efficient market:

$$E(r_{t+1}/I_t)=0 \qquad (2)$$

i.e. a zero expected rate of return, or in terms of price changes:

$$E(\Delta P_{t+1}/I_t)=0 \qquad (3)$$

i.e. a zero expected price change.

The fair game model comes from the martingale model which states that:

$$E(P_{j,t+1}/I_t)=P_{j,t} \qquad (4)$$

The martingale model says that if the price of a stock j, $P_{j,t}$ is a martingale the best forecast of price $P_{j,t+1}$ that could be constructed based on the current information I_t would just equal $P_{j,t}$, assuming that $P_{j,t}$ is in I_t. The martingale model implies that an investor with information I_t which may contain the history of dividends, earnings sale costs, even Macroeconomic data like G.N.P, Interest Rates or Money Supply will predict an expected rate of return an uninformed investor would predict, the martingale model says that the information set I_t is useless in predicting expected rates of return, in the sense that information I_t has been fully reflected on stock prices, Le Roy (1990).

According to Samuelson (1965), when we relax the assumption of a zero interest rate and also assume that agents have constant and common time preferences, common probabilities and are risk neutral, then they will always prefer whichever asset generates the highest expected return, completely ignoring differences in risk. If all agents are to be held willingly, as must be the case for equilibrium, all must therefore earn the same expected rate of return, equal to the real interest rate. Thus under the above assumptions the fair game model can be expressed as:

$$E(r_{t+1}/I_t)=\rho \qquad (5)$$

where ρ is the equilibrium rate of return equal to the constant real interest rate.

As mentioned above the fair game model assumes risk neutrality. Under risk neutrality, investors will always prefer to hold whichever asset generates the highest expected return, completely ignoring differences in risk. Risk neutrality implies the martingale but not the more restrictive random walk model. If agents do not care what the higher moments of their return distribution are, as risk neutrality implies, then they will do nothing to bid away serial dependence in the higher conditional moments of returns. Therefore risk neutrality is consistent with no zero correlation in conditional variances. The fact that future conditional variances are partly forecastable is irrelevant because risk neutrality implies that no one cares about these variances.

The fair game model is the link between fundamentalists and random walkers. Samuelson (1965), pointed out that that the rates of return on stocks are not without any structure. The fair game model implies that stock prices equal the discounted value of the expected cash flows these assets would generate. The derivation of the equivalence is as follows. Because (one plus) the rate of return is by definition equal to the sum of the dividend yield (d_t/p_t) and the rate of the capital gain (p_{t+1}/p_t) then (5) can be rewritten as:

$$P_t = \frac{E(d_{t+1}+p_{t+1}/I_t)}{(1+\rho)} \qquad (6)$$

Substituting t+1 for t (6) becomes:

$$P_t = \frac{E(d_{t+2}+p_{t+2}/I_{t+1})}{(1+\rho)} \qquad (7)$$

Using (7) to eliminate p_{t+1} in 6 and proceeding similarly n-1 times by assuming that $(1+\rho)^{-n} Et(p_{t+n})$ converges to zero as n approaches to infinity we obtain the N.P.V formula

$$P_t=\frac{E_t(d_{t+1})}{1+\rho}+\frac{E_t(d_{t+2})}{1+\rho}+\ldots\ldots. \quad (8)$$

Samuelson's result implies that fundamentalists are correct in viewing stock prices as equal to discounted expected cash flows. The only difference is that Samuelson instead of assuming that the price of a stock fluctuates around the fundamental value he assumed that the price actually equals the fundamental value. The importance of this is prominent; if price always equal the fundamental value, then no profit can be earned by trading on a discrepancy between the two, contrary to the fundamentalist assertion.

What looks striking here is that even though dividend changes can be partly forecasted, the martingale model says that rates of return cannot be forecast. The explanation of this "paradox" is that if the market expects dividends to rise, the price of stock will be high relative to its dividend yield now, so that when dividends rise no extra normal return will be generated. Stockholders will earn extranormal or subnormal returns only if dividends increase more or less than had been expected. Thus, if capital markets are efficient, a general expectation of a dividend increase does not imply that stocks should be bought or sold, since the expected increase is already reflected on market prices. Only new unanticipated information will affect stock prices, but since this information is random by definition its effect on prices will be a random deviation from today's best forecast.

Fama (1970), rejected the hypothesis that returns themselves are a fair game and proposed the following definition of market efficiency:

$$z_{j,t+1}=r_{j,t+1}-E(r_{j,t+1}/I_t) \qquad (9)$$

with $$E(z_{j,t+1})=E[r_{j,t+1}-E(r_{j,t+1}/I_t)]=0 \qquad (10)$$

In economic terms $z_{j,t+1}$ is the return at time t+1 in excess of the equilibrium expected return projected at time t, on the basis of the information set I_t, Fama (1970). In econometric terms the above model is:

$$R_t= \rho + \varepsilon_t \qquad (11)$$

where ε_t is the excess return with the properties $E(\varepsilon_t)=0$ and $Cov(\varepsilon_t,\varepsilon_{t-i})=0$ for i=1,2.....n.

With the additional assumption that the equilibrium return is constant through time then returns themselves are uncorrelated. The assumption that the equilibrium return is constant through time is crucial for empirical tests because as Leroy (1989) noted, *"On Fama's definition any capital market is efficient and no empirical evidence can possibly bear the question of market efficiency."*

Fama (1970),described an Efficient Capital Market as the market subject to the following theoretical conditions:

1. There are no transaction costs for the traded securities
2. All available information is costlessly available to all market participants.
3. all participants agree on the implication of current information for the current price.

Such a market though hardly exists in the real world. Does this imply that the world's stock markets are inefficient markets? The argument is that the above conditions are sufficient but not necessary for market efficiency. For instance the market may be efficient, if a sufficient number of investors have ready access to available information. Also, disagreement among investors about the implication of given information does not in itself imply market inefficiency, unless there are investors who can consistently make better evaluations of available information that is implicit in market prices. The Efficient Market Theory states that only factors not linked with future profitability, like investors psychology, should not affect stock prices.

1.4 Submartingales

Under the assumption of a non zero interest rate Fama (1970) suggested the submartingale model which has important practical implications for testing the Efficient Market Hypothesis. The submartingale model can be expressed as:

$$E(p_{j,t+1}/I_t) > p_{j,t} \qquad (12)$$

$$\frac{E(P_{j,t+1}/I_t)-P_{j,t}}{P_{j,t}} = E(r_{j,t+1}/I_t)>0 \qquad (13)$$

These models say that the price sequence $p_{j,t}$ of a security follows a Submartingale with respect to an information set I_t if the expected value of next periods price as projected on the basis of the I_t information set is greater than the current price or for the case of returns the submartingale model says that expected returns are always positive. The important practical implication of the Sub martingale model is that the non negativity assumption implies that no trading rule based on I_t can have greater expected profits than the Buy and Hold[1] strategy in the period in question.

1.5 The E.M.H. Restated

In the presence of risk aversion the fair game model property will not hold. Instead, we need a theory of equilibrium expected returns under conditions of risk. One such theory is provided by the Security Market Line of the Capital Asset Pricing Model. The Efficient Market Hypothesis can be restated in a different manner by using the Capital Asset Pricing Model (C.A.P.M.) as developed by Markowitz and Sharpe (1964). The C.A.P.M. states that in an Efficient Market the risk adjusted expected returns on all securities are equal; any differences across assets in expected rates are due to risk premia arising from unavoidable uncertainty which affects all securities, each at different degree, (systematic risk)[2].

The C.A.P.M. defines a simple measure of systematic risk a security contains, and this is its beta, (β), coefficient. Beta coefficients show how the return of the security covaries with the market return which is the return on all securities or the return of some representative index like the S&P 500 or the F.T index. If beta equals one the return on the security varies in one to one relationship with the market. If beta is greater than one, then the return on the security varies more than the market return. Finally, if beta is less than one, the return on the security varies less than the market return.

The beta can be estimated by a regression of the excess return on the asset ($R_i - r_f$) on the excess return of the market ($R_m - r_f$), assuming that the expected return on the asset is a linear function of the asset risk level, as measured by the beta coefficient. For every security the expected return should lie on the same straight line which is called the Security Market Line (S.M.L), and described by the equation:

$$E(R_j) = r_f + (ER_m - r_f)\beta_j \qquad (1)$$

This relationship represents the optimal forecast of a security's return. If the CAPM is expressed as a fair game :

$$z_{j,t} = R_{j,t} - E(R_{j,t} / \hat{\beta}_{j,t}) \qquad (2)$$

$$E(R_{j,t} / \hat{\beta}_{j,t}) = r_{ft} + [E\ (R_{mt} / \hat{\beta}_{mt}) - r_{ft}]\ \hat{\beta}_{jt} \qquad (3)$$

$$E(z_{j,t}) = 0 \qquad (4)$$

with $E(R_{j,t}/\hat{\beta}_{j,t})$ the expected rate of return of the j^{th} asset during this time period, given a prediction of its systematic risk $\hat{\beta}_{j,t}$. $E(R_{mt}/\hat{\beta}_{mt})$ the expected market rate of return given a prediction of its systematic risk, $\hat{\beta}_{mt}$. $\hat{\beta}_{jt}$ the estimated systematic risk for the j^{th} security based on past time period information set I_{t-1} and r_{ft} the risk free rate of return during this period.

According to the Efficient Market Hypothesis any deviation of the actual return R_j from the expected should be random. Discovery of a security whose expected return is above, (below) the S.M.L is an indication of market inefficiency, for that security is expected to give a risk adjusted return above (below) the required level, that is it is underpriced (overpriced) and consequently an investor can profit from this deviation.

2. Empirical Tests for Market Efficiency

Fama (1976), defined as an Efficient Market the market which:

1. It does not neglect any information relevant to the determination of the security prices.
2. It acts as if it has rational expectations.

Thus, the empirical research for market efficiency investigates if there is past available information which can help to predict future returns profitably, violating the fair game model but also investigates if factors not related with fundamental values influence stock prices.

Fama (1970), also has distinguished three types of Market Efficiency which are very useful for empirical tests. A market is Weak Form Efficient Market if the information set I_t contains only the history of prices. Semistrong Efficient if I_t contains all publicly available information. Finally, Strong Efficient if I_t contains every kind of possible information, including inside information. If a market is Strong form Efficient it is also Semistrong and Weak but the opposite does not hold.

Tests for Market Efficiency generally look for evidence suggesting that investors using a past information set could have earned excess returns by following some pattern of buying and selling which the information set would indicate. Such trading rules, as repeatedly stated before, should not exist in an efficient market. A strategy of simply Buying and Holding stocks should yield higher average returns when the transaction costs of buying and selling are taken into account.

Several attempts have been made in order to test Market Efficiency in the worlds stock markets. Two useful tools in testing the Market Efficiency proved to be the fundamental and technical analysis. In a Weak Efficient Market, Technical Analysis, is useless because price patterns do not exist. If the market is Semistrong Efficient then Fundamental analysis is useless. In an Efficient Market in an econometric model where the dependent variable is the return of a security the explanatory lagged variables should prove statistically insignificant implying that they have been already reflected on stock prices.

2.1 Tests for the Weak Form of Market Efficiency

Researchers have followed two different approaches in order to test the weak form of Market Efficiency. The first, approach relies primarily on common statistical tools. If the statistical tests tend to support the assumption of the random walk model for independence of price changes, one then infers that there are probably no mechanical trading rules or chartist techniques, based solely on patterns in the past history of price changes, which could make the expected profits of an investor greater than would be with a simple Buy and Hold trading strategy. The second approach to testing independence proceeds by testing directly different mechanical trading rules to see whether or not they provide profits greater than the Buy and Hold trading strategy.

2.1.1 Statistical Tools

For the statistical approach several statistical tools like descriptive statistics, dynamic regression, spectral analysis, runs tests have been employed to detect patterns in price changes. A part of the statistical research was centered on the nature of the distribution of price changes. Bachelier's model implied a normal distribution of price changes if transactions are uniformly spread over time and their number is very large. Work of Kendal (1953) and Osborne (1959,1962) generally supported the normality hypothesis but they observed higher proportions of large observations in their data distribution opposite from what would be expected if the distribution were normal.

It was suggested then that these departures from normality could be explained by a more general form of the Bachelier model. Fama (1965), proposed that non normal stable distributions are a better description of the distribution of daily returns since these distributions allow for thicker tails and thus can account for the above empirically observed feature of price changes distributions.

Some other studies were concentrated on other statistical properties of the stock price changes for example the serial correlation coefficients. Most of these studies found weak statistical dependence between successive price changes. In 1953, Kendal examined the behaviour of weekly changes in nineteen indices of British industrial share prices and spot prices of cotton and wheat. After extensive analysis of serial correlation he concluded that *"the series looks like a wandering one; as if once a week a demon of chance drew a random number from a symmetrical population of fixed dispersion and added it to the current price to determine next weeks price"*. Similar results of linear independence were reported by Moore (1962), Granger & Morgerstern (1963), Fama (1966,1970), Berkman (1978) and others. In some cases where the statistical relationships appeared to be significant profits based on the statistical relationships disappeared when transaction costs were taken into account.

Nierderhoffer and Osborne (1966), in another study used the "runs"[3] technique and reported two departures from complete randomness in common stock price changes from transaction to transaction. First their data indicated that reversals, pairs of successive price changes of opposite sign, are from two to three times as likely as continuations, pairs of consecutive price changes of the same sign. Second, a continuation is slightly more frequent after a preceding continuation than after a reversal.

Nierderhoffer and Osborne offered explanations for this phenomenon based on the market structure of the N.Y.S.E introducing thus the significance of the institutional settings when investigating the Efficient Market Hypothesis. Nierderhoffer and Osborne noticed that the three major types of orders an investor might place on a given stock in N.Y.S.E. were: 1.buy limit (buy at a specified price or lower) 2. sell limit (sell at a specified price or higher) 3. buy or sell at market (at the lowest selling or highest buying of another investor). When the above types of orders are unexecuted then the sell limit orders are at higher prices than the unexecuted buy limit orders. If we suppose that there is more than one unexecuted sell limit order at the lowest price of any such order, then a transaction at this price initiated by an order to buy at market can only be followed either by a transaction at the same price (if the next order is to buy), or by a transaction at a lower price (if the next market order is to sell). Consecutive price increases can usually occur when consecutive market orders to buy exhaust the sell limit orders at a given price. Even though the above two researchers presented convincing evidence of statistically significant departure from independence in price changes, no profitable trading rules could have been constructed on the basis of their findings.

2.1.2 Filter and other Trading Rules

In the field of mechanical trading rules the most notable is the work of Alexander (1961). The Alexander filter technique is a mechanical trading rule which attempts to identify patterns in stock prices if the trading rule yields profits.

An X per cent filter, e.g 10%, is defined as follows: If the daily closing price of a particular security moves up at least X per cent, buy and hold the security until its price moves down at least X per cent from a subsequent height, at which time simultaneously sell and go short. The short position is maintained until the daily closing price rises at least X per cent above a subsequent low at which time one covers and buys. Moves less than X per cent in either direction are ignored. In his article Alexander (1961) reported tests for filters ranging in size from from five to fifty per cent. In general, filters of all different sizes and for all time periods yielded substantial profits.

Mandelbrot (1963), pointed out, that Alexander's computations incorporated biases which led to serious overstatement of the profitability of the filters. In his later paper Alexander (1964), reworked his earlier results to take into account the source of bias. In the corrected tests the profitability of the filter technique was drastically reduced. In general the above kind of filter rules do not seem to work profitably when transaction costs are taken into account, Fama and Blume (1966).

Some other researchers, constructed the "relative strength" or "portfolio upgrading" trading rule. According to this rule we define the average price of a security in a time period, then we get the ratio of the price at time t to the past time period average price, and construct a portfolio with the n stocks with the highest price ratios. Then someone tries to keep in that portfolio the stocks with the highest prices ratio by buying and selling accordingly.

Generally, most of the tests for the weak form of Market Efficiency tended to support the proposition that price changes are random and that price histories are useless to forecast and forecast profitably price changes.

2.2 Tests for the Semistrong Form of Market Efficiency

In general the Semistrong Form tests of Efficient Market models are concerned with whether current prices fully reflect all obviously publicly available information. Researchers tried to develop trading rules on publicly available information and test if the trading rule yields an extra normal return. Such a trading rule may use economy wide information or information about individual firms or groups of firms like stock splits or financial reports of firms and industries, to come up with the appropriate times to buy or sell.

2.2.1 Regression Techniques

One method of testing the Semistrong form of market efficiency is to examine the price responses to announcements thought to be relevant to stock returns. The Semistrong form of Efficiency is supported if stock prices react only to the unanticipated part of any announcement and react quickly.

The above proposition can be tested with a model of the following form:

$$\Delta P_t = a_0 + a_1 F_{xt} + a_2 U_{xt} + \varepsilon_t \qquad (1)$$

where ΔP_t is the price change at time t, F_{xt} the forecast value of the explanatory variable in question, let us say x, from a survey or other source under the assumption of rational expectations, U_{xt} the actual value of variable x minus the forecast value and ε_t the error term under the O.L.S. assumption of white noise. The Semistrong form of the Efficient market hypothesis requires that a0=0 a1=0 a2≠0 as a test for rational expectations, Gowland (1986).

In the above model if someone adds past unexpected and forecasted values, these should prove statistically insignificant. The above type of model is a joint hypothesis test i.e., that the employed forecasts are the market's rational forecasts and the Efficient Market Hypothesis is a valid Hypothesis.

The problem with the above model is how to construct market expectations. Researchers have used statistical methods and survey approaches. The statistical methods are indirect and simplistic while the survey methods are limited since it is very difficult for someone to have the opinion of every market participant in order to construct the "market" expectation, and weight these opinions; not to mention the honesty of the survey subjects.

A more convenient test would be to investigate if the stock return at time t reacts to past and thus expected actual announced values of the proposed variables which affect stock returns.

$$R_{j,t}=a_0 + \sum_{i=1}^{n} a_i \bar{X}_{t-i} + u_t \qquad (2)$$

where $\bar{X}$ represents a vector of variables which affect stock prices. If statistically significant lagged variables exist, $a_i \neq 0$, in the above model and someone can profit from this finding then the Efficient Market Hypothesis is violated. Nevertheless, the majority of the studies using the above technique found that the stock market conforms reasonably well to the Semistrong form of efficiency.

For instance, Schwert (1981), analyzed the reaction of daily stock returns to the announcement of the C.P.I. inflation rate. Schwert found that the stock market reacts to the unexpected Inflation around the time when C.P.I. is announced but the reaction of aggregate stock returns to unexpected Inflation was not strong. The days following the announcement, the market seemed to react slowly to the news about unexpected Inflation but the magnitude of the reaction was too small not allowing for the formation of profitable trading strategy.

Some other researchers used as an explanatory variable Money Supply announcements and tried to see if stock returns react indeed to unanticipated changes of Money Supply announcements; and if any possible trading rule can be extracted from the tests they performed. Homa and Jaffe (1971) for example, supported the view that past increases in Money supply lead to increases in equity prices in agreement with Sprinkel (1964). Other researchers have shown that past money changes do not contain predictive information for stock prices, supporting thus the Efficient markets view, Rozeff (1974), Davidson and Froyen (1982).

Pearce and Roley (1983), tried to focus on the very short run response, (weekly), of stock prices to both anticipated and unanticipated announced changes in Money Supply. These researchers have found that stock prices reflect only the unanticipated change in the Money Supply and that the response is very quick in confirming the Efficient Market Hypothesis.

2.2.2 Event Studies

Some analysts used other Economic variables and different methodology, these studies are known as event studies[4], in order to test the market reaction to news.

Sunders (1973) used accounting information, Hong, Kaplan and Mandelker (1978) used mergers information while Black and Scholes (1974) dividends information.

One important study on this field of research is the work of Fama, Fisher, Jensen & Roll who tried to see the reaction of stock prices to announcements for stock splits. The presumption of this work is that splits may often be associated with the appearance of more fundamentally important information. The idea was to examine security returns around split dates in order to see if there is any inconsistent behaviour and in this case to determine to what extent it can be accounted for by relationships between splits and other fundamental variables. The above researchers found a different behaviour of stock prices during the period prior to the stock split. They suggested that when a stock split is announced the market interprets this as a signal that the company's directors are confident that future earnings should be sufficient to maintain dividends payments at a higher level. Thus, some large price increases they found in the months preceding a split may be due to an alteration in expectations concerning the future earnings of the firm. Examining the adjustment time of stock prices to information about stock splits the above researchers concluded that their results gave a considerable support to Market Efficiency. Most of the other studies which also examined the "announcement effect" of various variables on the return of the securities supported the Efficient Market Hypothesis as well, Aharony and Swary (1980) Brown, Harlow and Tinic (1988).

2.3 Tests for the Strong Form of Market Efficiency

2.3.1 Empirical Tests

The Strong Form tests for Efficient Markets are concerned with whether all available information is fully reflected on prices, in the sense that no individual has higher expected trading profits than others because he has monopolistic access to some information. Researchers have tested the strong form of efficiency in two ways,

1. by examining the returns of insider trading and
2. by evaluating the performance of Mutual Funds.

The evidence from the first type of tests does not support the Efficient Market Hypothesis, Baesel and Stein (1979), Finnerty (1976), Givoly and Palmon (1985). Legal inside trading consists of the buying or selling of a company's stock by an officer or director of the company. Such trading can be legal as long as it is not motivated by specific news about the company prospects that has not been announced to the public, although there are different laws for every country.

Nierderhoffer and Osborne (1966) have pointed out that the specialists on the N.Y.S.E. use their monopolistic access to information concerning unfilled limit orders to generate monopoly profits and other researchers indicated that officers of corporations sometimes have monopolistic access to information about the firms. In general, studies that have examined the returns to the legal insider trading have concluded that insiders make abnormal profits and hence that the stock market is not Strong Form Efficient.

The other type of tests, those which focus on the investment performance of Mutual Fund managers support the strong form of the Efficient Markets, Jensen (1968), Kon and Jen (1979). These tests assume that Fund managers are more likely to have access to private information or are better able to estimate the effects of information to stock returns. Thus if certain funds consistently earn abnormal returns even after accounting for the level of risk this would be an evidence against strong form of efficiency.

The major problem in using the Mutual Fund industry to test the Efficient Market model is the development of a "norm" against which performance can be judged. The norm must present the results of an investment policy based on the assumption that prices fully reflect all available information and the belief that investors are risk averse and so on average they must be compensated for every risk undertaken. Thus, one may have the problems of finding appropriate definition of risk and evaluating each fund relative to a norm with its chosen level of risk.

Apart the above problem, as already mentioned, studies comparing fund performance indicate no violation of the strong form of efficiency.

3. New Evidence

Research conducted in 1960'^{s} and 1970'^{s} generally supported the Market Efficiency. More recent evidence however does not support the same conclusion. The evidence now suggests, contrary to the prediction of the Efficient

Market model, that most fluctuations in stock prices can not be traced to changes in rational forecasts of future dividends. The recent evidence arises from two areas of research.

First, analysts came to realise that stock returns display a variety of systematic patterns, some kind of anomalies, which are difficult to be explained by the Efficient market hypothesis. Second, analysts realised that the same models which imply that returns should be unforecastable also imply that asset prices should have a volatility which is low relative to the volatility of dividends.

In the following section I am going to describe these recent empirical results and comment on the implications on the Efficient Market Hypothesis.

3.1. Calendar Anomalies

3.1.1 Weekend Effect

Several empirical papers investigating the Weak Form of Market Efficiency have concentrated on some calendar patterns. One of them is referred as the "Weekend effect". Research has given evidence that average stock returns have appeared to be lower on Mondays and higher on Fridays than on other days of the week, French (1980), Gibbons and Hess (1981).

This difference is an anomaly since the Efficient Markets model can not account for this systematic effect.

The Efficient Markets model would predict that returns should be higher on Mondays because Mondays return is for three days (Saturday, Sunday and Monday) than for one (Monday) if returns are generated continuously in calendar time; or the return is the same for all five days of the week if returns are generated in trading time.

The presence of such "day of the week" patterns can be investigated with models of the following forms :

$$R_t = C_0 MON + C_1 TUE_t + C_2 WED_t + C_3 THURS_t + C_4 FRI_t + u_t$$

(Trading time)

$$R_t = C_0 (1+2\ MON) + C_1 TUE_t + C_2 WED_t + C_3 THURS_t + c_4 FRI_t + u_t$$

(Calendar time)

where the variables TUE, WED,...FRI are dummy variables and u_t the error term under the assumptions of white noise.

The constant term (C_0) in the above models estimates the average return on Mondays. In the presense of the Monday effect the constant term should be significantly different from zero and negative as evidence of a lower Monday return while the other coefficients C_1, C_2, C_3, C_4 should be equal to zero.

Part of the "Weekend effect" may be due to the settlement practices of N.Y.S.E. When stocks are bought or sold transactions have five business days to settle, combined with the one day check clearing delay. This practice produces higher returns on Fridays and lower returns on Mondays to compensate for the extra two days of interest to buyers of stock on Friday, Lakonishok & Levi (1982).

French (1980), gave a different explanation for the "Monday effect". He argued that the information released over the weekend tends to be unfavourable. If firms for instance fear panic selling when bad news is announced, they may delay announcement until the weekend, allowing some time for the information to be "digested". It seems that the market participants failed to discover and embody on prices this information pattern or they realised that it is unprofitable. Trading rules based on the Weekend effect (Buy on Monday sell on Friday), generally did not appear to outperform the Buy and Hold when transaction costs, even small, were taken into account.

3.1.2 January Effect

Another calendar anomaly is the January effect. Researchers have found the return on holding stocks over January averages higher than for other months. The existence of the January effect can be examined by estimating a model that allows the average monthly stock return to depend on the month of the year like the following one:

$$R_t = d_0 JAN + d_1 FEB + d_2 MAR + \ldots\ldots + d_{11} DEC + u_t$$

where as before the variables FEB, MAR,... DEC are dummy variables and u_t white noise. If there exists a January effect the coefficients than the constant term, which stands for January, should be negative.

The January effect is often ascribed to investors selling stocks in December to realize capital losses for tax purposes and then rebuying stocks on January returning to desired portfolio compositions. However several problems have been connected with this explanation. Studies have shown that it is not optimal to wait until December to realize capital losses, Constadinides (1984). Moreover, the January effect appears to have existed before the imposition of income taxes in United States, Jones et al (1987). Also, investors with noncapital gain taxes, such as Pension Funds, should identify any depedency towards abnormally low returns in December and should become buyers of stocks oversold in late December, Fortune (1991).

3.1.3 Wednesday Effect

In addition to the above calendar anomalies, we can refer to the "Wednesday effect". In 1968 the N.Y.S.E. was closed on Wednesdays in order to allow the back offices of brokerage houses to catch up with the paper work. Roll (1986), found that the volatility of stock prices was lower from Tuesday to Thursday when the market was closed on Wednesdays than over two day periods during which the exchange was not closed. This is an evidence against the E,M.H because of the reason that as much news about fundamentals is generated on Wednesdays as on other weekdays. This Wednesday effect suggests that it is the trading process itself rather than news, that generate price changes.

3.1.4 Day of the Month Effect

Finally there exists a "day of the month" effect. Stock returns are positive in the days surrounding the turn of the month but are zero on average for the rest of the month, Ariel (1985).

3.2 Non Calendar Anomalies

3.2.1 P/E Anomaly

There are some studies which have found again some kind of "anomalies" which are not of the calendar type presented above; the price/earnings (P/E) anomaly, Basu (1977,1983), is the most prominent. The P/E anomaly refers to the finding that stocks with low P/E ratios generate systematically higher rates of return than do stocks with high P/E ratios. Since last period's P/E ratio is publicly available information excess returns on portfolios chosen by picking stocks with low P/E ratios violate Semistrong Efficiency. Moreover such a finding implies that investors overreact to news about a firms earnings, being either too optimistic and bidding the price earnings ratio too high or too pessimistic and causing the price earnings ratio to fall too low.

3.2.2 Winners Losers Anomaly

De Bondt & Thaler (1985), have documented a pattern similar to the P/E anomaly. They compared fictional portfolios of "winners", stocks that had appreciated significantly in the recent past, with similar portfolios of losers. They found that the losers strongly out performed the market generally in the subsequent years while winners earned lower returns than the market averages.

3.2.3 Small Firm Anomaly

Another anomaly is the "Small Firm Effect", in which small firms appear to earn higher returns than large firms, Banz (1981), Reinganum (1981), Lustiq and Leinbach (1983). In addition, these abnormal returns were concentrated in January, Keim (1983), Reinganam (1983).

One interpretation of this finding is that small firms are riskier and hence should earn a higher average return. The pattern though appeared even when an allowance was made for differences in riskiness. Additionally the above explanation does not account for the fact that the excess return is concentrated in January.

If the above anomaly can be referred to the January effect one can say that since small firms have more variable prices it is more likely for an investor to experience capital losses and hence more likely for the small firm stock to be sold at the end of the year for tax purposes.

3.2.4 Value Line Anomaly

Still another puzzle is the Value Line anomaly, Holloway (1981), Copeland and Mayers (1982). The Semistrong type of Market Efficiency implies that investment advice based on public information should be worthless. The Value Line Investment Survey, the largest advisory firm in U.S, uses this kind of information to rank stocks by their expected returns In an Efficient Market one could not benefit from the Value Line recommendations. Several studies have documented, however, that investors following the Value Line recommendations would have earned abnormally high returns, but also that frequent trading based on the Value line recommendations would result high total transaction costs which eliminate the abnormally high returns.

3.2.5 Closed End Mutual Funds Anomaly

Finally, another well known anomaly involving a specific class of firms is the "Closed End Mutual Fund" puzzle, Malkiel (1977). Closed End Mutual funds differ from Open End Mutual Funds in that Open End Mutual Funds keep the prices of their shares at the Net Asset Value by promising to buy or sell any amount of their shares at the Net Asset Value. Closed End Mutual funds on the other hand, issue a fixed number of shares at inception, and any trading in those shares is between investors. This allows the Closed End Mutual Funds share price to deviate from the

Net Asset Value, that is Closed End Mutual Funds can trade at either a discount or a premium.

If the Efficient Market Hypothesis is valid then any sustained discount or premium on Closed End Mutual Funds shares must be due to unique characteristics of the Fund. In the absence of such distinguishing characteristics, any discounts or premiums would indicate investors to engage in arbitrage that would eliminate the discount or premium. For example, an unwarranted discount would lead investors to buy the Closed End Mutual Fund shares and sell short a portfolio of stocks identical to that held by the fund, capturing thus a riskless increase in wealth equal to the discount. A premium on the other hand would indicate investors to sell short the Closed End Mutual Fund and buy an equivalent portfolio of stocks. But the Closed End Mutual Funds typically sell at discounts, and the discounts are often substantial. The discounts move inversely to stock prices. Periods of "Bull" markets are associated with low discounts, while "Bear" markets are associated with high discounts. Thus the price paid for a dollar of Closed End Mutual Funds assets may be influenced by psychological factors.

Several explanations have been offered for the Closed End Mutual Funds discounts. The first relies on potential capital gain taxes on unrealised appreciation. A new buyer of Closed End Mutual Fund shares faces a tax liability if the fund should sell appreciated securities; this potential tax liability justifies paying a lower price than the market value of the underlining securities. Second, Closed

End Mutual Funds might have limited asset market liability if they buy privately placed debt which can not be sold to the public without incurring the expense of obtaining Securities and Exchange Commission approval. Third, agency costs, in the form of high management fees or lower management performance might explain the discounts. Malkiel (1977), found that the discounts were larger than could be associated for by the above factors giving evidence that the Closed End Mutual Funds is an irrational anomaly.

4. Modern Rationality or Volatility Tests

In fact volatility tests are tests for rational expectations. Shiller (1981), argued on prices volatility as follows: Suppose that investors have perfect foresight so that they could predict dividends without error. According to the fundamental model the price investors would be willing to pay for the stock would be the present value of the known future dividends. Assuming that the rate at which investors discount future dividends is constant Shiller constructed a series of stock prices P_t^* that would have resulted under the assumption of perfect foresight.

According to the Efficient Market Hypothesis the actual stock prices Pt are the optimum forecasts that investors can make under their limited information of the perfect foresight prices. Shiller notes that optimal forecasts of economic variables should vary less than the variables themselves because the optimal forecast is a weighted average of discounted future values of the variables; thus they cancel out any fluctuations in that variables. So he concluded that the variance of the actual stock prices should be less than the estimated variance of the perfect foresight series he conducted.

Assuming a constant discount rate and that P_t is a forecast of P^*_t so as:

$$P^*_t = P_t + \varepsilon_t$$

Under the Efficient Market Hypothesis P_t is the optimal forecast of P^* which implies that ε_t must be uncorrelated with P_t.

Thus taking the variances,

$$VAR(P^*_t) = VAR(P_t) + VAR(\varepsilon_t)$$

Since the variance is always positive the above implies that the variance of the perfect foresight price must exceed the variance of the actual price.

Results of tests on the volatility implications of Market Efficiency were circulated in a paper of Le Roy & Porter (1981). Shiller (1981, 1984) presented identical results as well. In both cases asset prices appeared to be more volatile than is consistent with the Efficient Market hypotheses. There may be two possible sources of the excess volatility in stock prices. First, investors could be overreacting to relevant information; second, they could be reacting to information which is irrelevant according to the Efficient Markets model.

Nevertheless, the authors interpreted their results differently. Shiller's view was that his results may be viewed as an evidence against market efficiency and in favour of the existence of elements of irrationality in security pricing or time varying expected returns "*Other possibilities are that ex ante real interest rates show very large movements or alternatively that the market is irrational and subject to fads.*" Shiller (1981). LeRoy and Porter characterised the violations merely as an anomaly requiring explanation, LeRoy(1990).

Shiller found that the variance of the actual prices (optimal forecasts), was about six times the variance of the fundamental value (perfect foresight prices).

Shiller's discovery implies either that the Efficient Market Hypothesis is invalid or his test is invalid. This is a common problem for statistical tests, one must take assumptions about the world in order to construct any test, but one can not know whether rejection of the null hypothesis he constructed is due to invalidity of the hypothesis or to the invalidity of the assumptions. The argument in the case of volatility tests is the same as before when we discussed the tests for the Semistrong form of the Efficient Market Hypothesis. In the Semistrong form models when the variable which represents the forecast of the market proves to be statistically significant itimplies either Market Inefficiency or that the variable which the researcher uses for the market forecasts, even when pass the rational forecast tests, does not represent the real forecast which the market forms.

Several researchers contradicted the view of Shiller based on the statistical properties of these tests. Marsh and Merton (1986), argued that if Shiller's assumption that dividends are a stationary time series is relaxed and instead assume that the process by which dividends are set is non stationary, then the Efficient Market Hypothesis is reversed: under the Efficient Market Hypothesis market prices should be more volatile that perfect foresight prices. Nevertheless, tests which have taken into account nonstationary dividends confirmed the results of the early work. Kleidon (1986), has also critisised the excess volatility tests on statistical grounds, arguing that the Shiller test is an asymptotic test, assuming a very large sample of observations over time, and that the data available are necessarily finite, hence small sample bias can weaken the test.

Some other researchers argued that the comparison of variances is inappropriate because the variance of P_t^* depends on all actual future dividends whereas the variance of P_t depends only on information known at time t and that an appropriate comparison is between variables based on the same information.

Finally, an assertion on Shiller's work is that he assumed a constant discount rate. In contrast some researchers argued that in a world with risk averse investors the rate of return should vary accordingly with the state of the economic variables.

The volatility tests is still an area of research. and empirical studies have shown that volatility results can be used as the basis for for a profitable trading rule, Bulkley and Tonks (1989). Despite the criticisms, the excess volatility tests provide an additional serious reason, other than the observed anomalies, to doubt the Efficient Market Hypothesis.

4.1 "Noise" in Capital Markets

As already mentioned, the excess price volatility can be explained from the fact that investors could be reacting to information which is irrelevant to stock prices and that forces other than rational forecasts of future dividends to influence stock prices.

Roll (1988) investigated the irrelevant information source of excess volatility and reported results of tests of whether the Efficient Market model provides accurate ex post explanations for stock price movements. He found that irrelevant information appeared to be of dominant importance. Even using such data as industry average prices and aggregate stock market indexes, Roll was able to explain only a small fraction of the variances in prices of individual stocks. Cutler et al (1989) provide also evidence that stock returns are unrelated to news.

Prior to Roll, Black (1986), in his presidential address in the American Finance Association used the term noise. According to Black, noise *"in the sense of a large number of small events"* which *"is often a causal factor much more powerful than a small number of large events".* According to Black noise makes trading in financial assets possible and thus allow as to observe prices for financial assets. Noise is included in some people information set since Black believes that *"differences in information not opinion create the trading."* Black redefined the Efficient Market as *"a market in which price is within a factor of two of value i.e. the price is more than half the value and less than twice the value. The factor of two is arbitrary" "By this definition I think almost all markets are Efficient, almost all of the time. Almost all means at least 90%"*

Noise theory was applied to explain some of the mentioned market anomalies. For instance, misperceptions about the returns of the Closed End Mutual Funds caused by noise become a source of risk for any short horizon investor trying to arbitrage the difference between the fund and its underlying assets if more noise will make the discounting wider in the future. Such risk leads to the market discounting of Closed End Mutual Funds even if noise on average will be zero.

4.2 19, October 1987

In addition to the above presented evidence, some recent events like the massive international seloff on October 19,1987 rise more questions about the determination of prices in the world's stock markets and gave more evidence for the existence of noise. Research on the October 1987 crash indicated that the market was influenced by non-rational factors (Barro, 1989).

Fama (1989), set the question whether the price decline of 1987 was irrational or whether it was a rational adjustment to a new equilibrium, that is, to rational perceptions of changes in fundamental values and if it was irrational what changes in market structure can make pricing more rational during similar future episodes. In a market economy prices are signals of resource allocation. rational prices, prices that are unbiased estimates of fundamental values, contribute to economic efficiency by directing resources toward their highest value uses. The common valuation models assert the view that rational prices have two sources, namely changes in expected earnings and changes in the discount rates used to price expected earnings.

Concerning the first part it seems that the 1987 crash had a large irrational component. The reason is that there was no news immediately preceding October 19 that would seem to imply a decline more than 20% in fundamental values. Mandelbrot (1966) argued that rational forecasts of economic conditions, depend on past conditions. Specifically, the longer a period of good or bad times has run, the longer it is rational to forecast that it will continue. In a period of continuing good times, security prices will be high relative to observed earnings or dividends because prices rationally forecast extended good times. The crash was preceded by a long period of sustained growth confirming the 'irrationality' of the event. Some other people argue though on an underlying "trigger" to the crash like the U.S trade deficit, anticipation about the 1988 U.S elections or fears about recession, or the German monetary policy.

Noise, "volatility unrelated to variation in fundamental values", has been linked to the October crash. Among the most popular explanations are those related to the U.S and other countries institutional structure and practices e.g. computer-assisted trading, portfolio insurance, the organized exchange specialists, the auction system itself, margin rules and the absence of circuit breakers such as trading suspensions and limitations of price movements.

Roll (1989), did single variable and multiple regression analysis in order to see which institutional factors contributed to the crash. He found that official specialists, computer directed systems, price limits and margin requirements were associated with less severe stock market declines in October 1987 and that the presence of a continuous auction system and automated quotations were associated with larger declines. Also variables like forward trading, options and futures trading, transaction taxes and trading off the exchange were unrelated to the extent of the crash.

4.3 Bubbles in Asset Prices

Many observers assigned the October crash to the bursting of a bubble. They pointed out that stock prices had risen so rapidly in 1986 and 1987 that a bubble surely existed. Clearly a bubble is not merely a random deviation of price from value, for the law of large numbers suggests that purely random deviations will wash out over time without any necessity of collapse.

The notion of the bubble is the difference between the fundamental value of an asset and its market price. Bubbles are self fulfilling departures of prices from fundamental values which continue until, for some reason, the conditions of self fulfillment disappear, Kindleberger (1978), Flood and Hodrick (1986), Diba and Grossman (1988), Camerer (1989). The bubble term enters to the stock price determination formulae in the following way:

$$P_t = \sum_{i=1}^{\infty} \frac{E(D_{t+1})}{(1+r)^i} + B_t$$

where $B_t = (1+r)B_{t-1} + z_t$ and z_t is "white noise".

Investors do not care if they are paying for a bubble because they expect to get the required return on that investment, in this sense bubbles often called "rational bubbles". The definition of a "rational" bubble implies some very strong restrictions on bubbles. One is that bubbles can not be negative. A negative bubble will become more negative at rate r and thus must ultimetly end in a zero price, a result that, once acknowleged must lead to the elimination of the bubble. Since there is no upward limit on prices a possitive bubble can exist. Nevertheless if investors understand that a possitive bubble means that the bubble must be an increasingly important component of price, they will imagine that at some time the bubble must burst. But as soon as they realise that it must burst it will burst.

If a "rational" bubble can hardly or never emerge what is left to the notion of bubbles? A crucial assumption of the bubbles can not exist paradigm is that investors behave as if they have an infinite time horizon. Nevertheless, if investors have finite time horisons then the resale price of their assets becomes a major determinant of their investment decisisons and a bubble can emerge.

In this sense bubbles theory is the essence of the "Greater Fool" explanation of speculative episodes under the assumptions that investors use a finite horizon valuation model and that the resale price is major determinant for the price someone pays for the asset i.e., you will knowingly pay a price above fundamental value because you believe that someone latter on will pay an even greater premium over fundamental value, creating thus a bubble in the price of the asset. The "rational" bubbles are realistic descriptions of stock price performance; if the stock market horizon is shorter than the time to the popping of a bubble the bubble can continue.

Hence a necessary condition for the existance of a speculative bubble is a finite time horizon. This is not however sufficient. Tirole (1982), has shown that even with a finite time horison, a bubble can not exist if expectations are rational, that is if investors forecasts are optimal. Hence bubbles require both finite time horizons and non optimal forecasting. Stated differently bubbles require inefficient markets.

4.4 Fads in Asset Prices

A special kind of non rational bubble and consequently another evidence against the efficient market hypothesis, is the so called fad, Camerer (1989). Fads theory investigates the possibility that prices drift away from intrinsic values because social forces create fads or fashions in asset markets.

We can define a fad as a deviation between prices and intrinsic value, Ft, which slowly reverts to its mean of zero.

$$P_t = \sum_{i=1}^{\infty} E(D_{t+1})/(1+r)^i + F_t$$

with $F_t = CF_{t-1} + z_t$ and z_t is white noise. The term C is a parameter measuring the speed of convergence or decay of the fad, Fama and French (1988).

It is useful to distinguish three type of fads theoretically, depending upon where faddishness is located. First, prices may fluctuate because the utility people get from holding assets varies over time, as if their psychic dividends are some function. Second, prices may fluctuate because of mass changes in beliefs about future intrinsic values. Third, prices might fluctuate because of fads in expected returns. It is worth notingthat fads in utilities or returns implies that fads are utility maximizing and thus in a limited sense rational, though belief fads are not rational, Camerer (1989).

Fads theory was applied in order to explain the stock market anomalies. For instance the winners-looser anomaly can be explained by the fad term which slowly reverts, DeBondt and Thaler (1985,1987). For the winners-looser anomaly price changes are correlated positively for short horizons and negatively for long horizons. This finding known as mean reversion has also been observed by other researchers, (MacDonald and Power). Most of them report positive autocorrelation of returns at high frequencies and a negative autocorrelation at low frequencies, Poterba and Summers (1988). Such non-independent price changes series indicate that prices may be driven driven by fads under the assumption of a constant equilibrium return. Nevertheless, if equilibrium expected returns vary over time, returns also vary over time in an efficient market. Indeed, if real interest rates are mean reverting, stock prices will also be mean reverting.

Real interest rates could vary for a variety of reasons. For a given riskless interest rate, changes in the riskness of stocks or in investors' tolerance for risk would cause the risk adjustment factor; and therefore the real interest rate to change. Alternatively, for a given risk adjustment factor, the riskless interest rate may change over time. Nevetheless Poterba and Summers (1988), argue that changes in the riskless of stocks or the risk tolerance of investors can not explain the mean reversion in their data because the degree of mean reversion they report implies changes in the riskiness of stocks or in the risk tolerance that are implausibly large.

4.5 Chaos Theory in Capital Markets

Recently, the concept of the efficient market hypothesis has been challenged by the new science of complexity referred to as "chaos theory". Chaos can result from non-linear dynamic systems. Dynamic system is every mathematical model which includes a time dimension. Non linear is the model in which the variables are related in a way other than linear. Chaos is the situation in which for some paremeters, the motions of a model system are so unstable and complicated that they look like random, and in fact pass the randomness tests, but in reality they are subjectto the law of the model system itself.

Chaos theory recognise the complexity which characterises the financial markets and takes into account factors which the efficient market hypothesis does not take like human irrationality and psychology, Peters (1991). Nevertheless, the chaos theory is consistent with the implication of the efficient market hypothesis that prices are unforcastable. Chaos theory says that accurate forecasts of the system are impossible at least because of technology limitations.

The simplest mathematical model which can describe the basic elements of chaos complexity is the logistic map described by May (1976) with the equation: $X_{t+1}=\rho X_t (1-X_t)$. For some small values of ρ the equation tends to stabilize at some number e.g for ρ=2.7 the number will be 0.6292. For some other larger values of ρ the system behaves in a random (chaotic) way and then stabilizes at some kind of periodic numbers (e.g for ρ=3.5 and X=0.4 the system in the beginning behaves chaotic and then appears a four period cycle; i.e every solution of the system appeared after three other solutions which in their turn appeared in the same four period cycle, (x,y,z,w,x,y,z,w,x,y,z,w,...). As ρ continuously but slowly increases the cycles appear more quickly 4,8,16,32,.. and suddenly intercepted by random numbers. Then as the procedure goes on appears an odd number periodicity i.e a cycle of three and then this periodicity starts to double 6,12,24 and then intercepted by a new random numbers. In chaos there is order and vise versa, these two meanings are linked in a mysterious way.

Apart from complexity another characteristic of chaotic systems is their sensitivity to the initial conditions of the system. Assuming that stock prices are generated by the above logistic map equation then when simulating the above stock market model we have to give some initial value let us say X. Let us now assume that the initial value is not X but X+e where e is a very small real number like 0.000000001. This small difference will produce quite different price movements in our model. In the beginning the two graphical representations of the model, one with X and the other with X+e, will be the same. After a while they will start to deviate slightly one from the other and then we observe two different graphs. Thus in two stock markets which on 1/1/aa have started with prices X and X+e after a week the same stock will have two different prices.

Let us also say the the two stock markets start with the initial value of X+e and a financial newspaper considers e tootrivial for printing, Mr J.M.K the investor who plays the stock market game every morning from his bed with the help of a computer in which he feeds data from the financial newspaper, if he decides to play after some days based on the initial value of X printed by the newspaper and even he knows exactly the model of the price behaviour he may find him self deep in red.

The practical implication of the above chaotic characteristics is that it is impossible for someone to forecast a chaotic system even if he knows the model equations and the initial parameters, simply because computers, even the modern ones, have limited digit precision (e is a too distant digit and they omit it in calculations).

Finally, chaotic models are characterised by a long memory effect. The long memory effect implies that if a series like stock prices is chaotic it will becharacterised by cycles. Mandelbrot named these periodicities as the Joseph effect reffering to the biblical story where Joseph interpreted Pharaoh's dream to mean seven fat years followed by seven lean years. The long memory effect in a financial market implies that information received today continues to be discounted by the market after it has been received. This is not simply serial correlation where the impact of information quickly decays. It is a long memory function; the information can impact for very long periods into the future. The above mentioned cycles, nevertheless, are non periodic and can not be detected with a conventional periodicity analysis like Spectral analysis.

Chaos theory includes a statistical analysis related to fractal geometry. This statistical analysis challenges the efficient market hypothesis and specifically the mathematics tied to Random Walks, and the normal probability distribution which is its basis. The Random Walk model of the E.M.H says that successive price changes are independent and that they are described by the normal distribution. However it has been well documented for over thirty years that realized market returns are not normally distributed. The frequency distribution of returns, as mentioned in the Martingale analysis, has a higher peak at the mean and fatter tails than the normal distribution. Despite this, returns continue to be described as "approximately normal". Fortunately, there is a family of probability distributions which are characterized by a high peak and fat tails. Benoit Mandelbrot suggested that market returns might be better described as a family of self similar distributions which are called fractal distributions or stable Paretian distributions.

Fractal distributions have two important characteristics coming from the chaotic models. The first one comes from the long memory effect. There will be long run correlation between observations. Also, in fractal distributions, variance becomes infinite or undefined. It is therefore unstable. The fact that variance is no longer defined also brings into question the modern portfolio theory which generally uses variance as a measure of risk.

Some researchers in an effort to exploit chaotic behaviour applied a statistical analysis (Rescaled Range Analysis)[5] to various capital markets and economic time series. I have to note here that statistical research for chaos demands a very large amount of data points. Some authors argue that the number of 5,000 data points to represent a lower bound, while some others consider 500,000 data points.

Edgar Peters (1989), found that stock price series are characterized by long memory effects and he reported a memory length of about four years. This memory length was independent of the resolution of the data. That is daily, monthly and quarterly data all exhibit the same four years cycle. In order to ensure that a long memory effect was responsible for the above finding, he scrambled the data. If a long memory effect was not causing these results, then the results should not change. However in all cases scrambling the data resulted in readings consistent with an independent process and the cycle length was also no longer apparent. Changing the order of returns destroyed the structure of the original series.

In another study Tata and Vassilikos (1991), they use again scrambled and unscrambled time series of foreign exchange and stock market returns and they tried to detect deterministic chaos. The argued that they did not have any evidence of chaotic behaviour in their data set.

5. Summary

The Efficient Market Hypothesis states that prices fully and very quickly reflect all available information so no one can earn excess profits based on that information. According to the Efficient Market Hypothesis prices should react only to the unanticipated news, but since this news is unforestable, by definition, price change must be unforecastable.

Early empirical work supported the above hypothesis. Nevertheless, recent studies in stock price behaviour report several deviations from the implications of Market Efficiency. First, researchers report a mumber of calendar and non calendar anomalous findings which can not be explained in the framework of the Market Efficiency. Second, it is argued that prices do not react only to information but there are other factors which influence stock prices like investors psychology. Finally, chaos theory and it's complexity recognises these non-rational factors but chaos theory is in line with the Efficient Market Hypothesis that prices are unforecastable.

After a century of debate the efficient market hypothesisis still an open issue and I think that there is much more to be said in the future because " *εν οιδα οτι ουδεν οιδα* " (I know one thing; that I know nothing) Socrates 500 B.C. Athens.

Notes

1.

Buy and Hold is the passive investment strategy to Buy securities and hold them without trading until liquidation. Then the value of the investment is calculated by the price at the time of liquidation. The Buy and Hold strategy when chosen assumes that the capital market does not misprice securities or if it does the investors do not have the ability to detect and exploit profitably this mispricing.

2.

The risk that can potentially be eliminated by diversification since it is specific to each stock is called unique or residual or diversifiable risk. The market or the systematic or undiversifiable risk is the risk which stems from the fact that there are Economy wide perils which affect all stocks. This kind of risk can not be eliminated with diversification.

3.

The runs test are concerned with the direction of changes in time series. The changes may be plus, minus or zero signs, and therefore, the series of numbers (changes) are replaced by the series of symbols. Hence, a run is defined as a sequence of like signs and its length is the number of like signs. There are also sequences and reversals in a time series. A sequence occurs when for instance a plus sign is followed by a plus one. A reversal occurs in the case where a plus sign is followed by a negative one. For example the series + + + + - + - - + + + - - - + +, is considered to comprise seven runs , nine sequences and five reversals. If there is a tendency for a series for a movement in one direction to be succeeded by a further such movement, then the average length of the run will be longer and the total actual numbers of runs will be less than if the movements were distributed randomly.

4.

The event studies examine if the return at any period is related only to the information relished during that period i.e

$$I_{t-1} \longrightarrow AR_{t-1}$$

$$I_t \longrightarrow AR_t$$

$$I_{t+1} \longrightarrow AR_{t+1}$$

where Ar stands for the stock's abnormal return and the arrow indicates the relation between information and abnormal return.

The abnormal return of a security is defined as $AR=R-R_m$ where R_m is the market return. According to the efficient market hypothesis a stock's abnormal return at time t should reflect only information relished at that time. Abnormal returns must be on average zero confirming thus the fair game model. Many researchers used the Cumulative abnormal returns CAR. After the announcement of a relevant economic variable the CAR should stabilise at the level they had at the day of the announcement or make a jump at the day of the announcement and then again stabilise. In the case where the CAR slowly increase or decrease after the day of the announcement this can be interpreted as a slow reaction of the market and possible violation of the efficient market hypothesis.

5.

A method developed in order to determine long memory effects. A measurment of how the distance covered by a particle increases over longer and longer time scales. For Brownian motion, the distance covered increases with the square root of time. A series that increases at a different rate is not random.

The Hurst exponent (H), is a measure of bias in fractional Brownian motion. H=0.5 for Brownian motion; 0.5<H<or=1.00 for persistent or trend reinforcing series; 0<or=H<0.5 for an antipersistent or mean reverting system.

TESTING THE WEAK FORM OF EFFICIENCY IN THE ATHENS STOCK ECHNAGE

Chapter Two

1. Testing the Weak Form of Market Efficiency in the Athens Stock Exchange

Overview

According to the Efficient Market Hypothesis (E.M.H), when a market is Efficient in the Weak Form, prices fully reflect all available information contained in the record of past prices; i.e., past prices do not contain any useful information which someone can use in order to forecast the current price change.

In the following analysis I will try to investigate if the stock price behaviour in the Athens Stock Exchange, (A.S.E.) is consistent with this form of the Efficient Market Hypothesis. If past price information prove statistically significant I will try to find a statistical model, with some predictive power, which will describe the data better than the white noise process. In the model formation I will use the Box-Jenkins approach which is a suggested technique for making short run forecasts.

Nevertheless, the Box-Jenkins models are not appropriate for exploiting regularities of low frequencies (periodicities of long cyclical movements). In order to exploit such periodicities, if any, I will use Spectral analysis which is very useful in cases where someone examines a great number of data points.

If the statistical analysis suggests market inefficiency, (violation of the fair game model) I will try to form a trading rule based on the statistical results. If such a trading rule proves to be profitable when compared tohe Buy and Hold strategy, then I have to conclude that the Weak form of Market Efficiency appears inconsistent with the data, under the assumption of a constant ex ante real interest rate.

1.1 The Data

In order to perform the above tests for Market Efficiency I chose eight, of the most active in trading terms, stocks from the Athens Stock Exchange (A.S.E), of which five represent banks and the rest three industrial firms. The time period examined is five years, from 1982 to 1986, and the observations are daily closing prices, adjusted for stock splits, resulting an amount of 1248 observations for each stock. In particular the banks are:

1.Bank of Greece 2.Commercial Bank 3.Ionian Bank
4.National Bank of Greece 5.Ergobank

The industrial firms are :

1.Lipasmata (fertilizers) 2.Piraiki (textiles) 3.Halkidos (cements).

Daily observations is a very interesting data set for someone when testingthe efficient market hypothesis. It is argued that high frequency data are rather noisy data and thus it is hard to observe some evidence against the efficient market hypothesis in terms of prediction, Fama (1970). Nevertheless, some other people argue that the shorter the observation period the more likely there is to be evidence for inefficiency because the market can not be expected to react truly instantaneously. Nevertheless, an advantage of using high frequency data is that we can avoid to some extend the problem of temporal aggregation and thus we may obtain more acqurate statistical results for the predictive validity of the models which may emerge.

It should like to note here that the A.S.E was closed for some days in the examined period for reasons like national holidays or strikes. It was possible for me to find the regular days (holidays) the A.S.E was closed but it was not possible to find the other days it was closed since there are not available records in the statistical department of the A.S.E. The number of irregular days the A.S.E was closed though is very small in comparison with my sample and I do not think that this can affect the statistical properties of my series. It should be noted however that my findings could not account for any possible calendar explanation (i.e., Monday effect), since the calendar sequence of the data changes whenever the Athens Stock Exchange was closed.

2. An Econometric Analysis of the Price changes in the Athens Stock Exchange

2.1 Regression Tests for Rationality

The most common way to test the Weak Form of the Efficient Markets Hypothesis is to investigate if there is any any significant statistical relationship between the current and past price changes, i.e., the information set in question is $I_{t-1}=[\Delta P_{t-i}]$ with i=1,...n. If it does not appear to be any such relationship between them, then the Weak Form of Efficiency will have support from the data.

In fact, the above proposition is a test for Muthian rational expectations of the weak form. Around 1960, Muth suggested that theories of expectation formation, should be consistent with the economic model being considered, in this case we consider the Efficient Market Hypothesis. Specifically, Muth (1961) suggests: "*I should like to suggest that expectations, since they are informed predictions of future events, are essentially the same as the predictions of the relevant economic theory. At the risk of confusing this purely descriptive hypothesis with a pronouncement as to what firms ought to do, we call such expectations rational*". The prediction of the Efficient Market Hypothesis is that price changes result from news flowing in the market. Since news is unpredictable by definition and since there is no reason to believe that news does not come in the market in a random way, price changes should be independent and unpredictable.

The rational expectations test procedure runs as follows: Let Y_t^* denote the expected value of an actual variable Y_t (in our case the variable is the price of a security), then rationality implies that the current forecast error $(Y_t-Y_t^*)$ is uncorrelated with variables in the information set I_{t-1} when the forecasts are formed. The above proposition implies that when forecasts are formed all relevant information has been taken into account.

Thus, in a model of the form:

$$Y_t - Y_t^* = a_0 + a_1[I_{t-1}] + \varepsilon_t \quad (1)$$

we should have $a_0=0$ $a_1=0$ Maddala, (1988).

When I_{t-1} includes information contained in the history of prices, (like past price changes), then the test as mentioned before is called weak test for rationality. The strong version says that the forecast error $(Y_t^* - Y_t)$ is uncorrelated with all the variables known to the forecaster. This test is a test for the Semistrong version of the Efficient Market Hypothesis and will be discussed later.

One important aspect of these tests which I would like to mention here, since it is closely related to the test whether the Efficient Market Hypothesis holds or not, is the question of what variables should one include in the information set in order to test the Efficient Market Hypothesis. It is argued that when some lagged variable proves to be statistically significant in explaining the stock price behaviour, then this would imply that either the Market is inefficient with respect to that variable or that the variable in question is not included in the information set of the market.

It has been argued that the variables to be included in the information set, when the Efficient Market Hypothesis is tested, should depend on the costs and benefits. It is true that past values of the variable forecasted are readily available and should be in the information set, but the same can not be said for other variables. It has been emphasized, Feige and Pearce

(1976), that agents with economically rational expectations will set the marginal cost equal to the marginal benefit of acquiring information. In practice, however, since these costs and benefits are difficult to observe, it is hard to say what the information set ought to be. For this reason when I examine the Market Efficiency I will use practically free information which is always readily available to investors.

In order to test the above Efficient Markets "consistent model", I used dynamic regression analysis. In the models under test, the dependent variable takes the form of the price change at time t, since at that time it is considered as unanticipated, random walk model, and the explanatory variables are the lagged values of the dependent variable. In order to test for any possible relationship between the dependent and the explanatory variables I used standard statistical criteria like the R^2, which measures the variation of the dependent variable which can be explained by the independent ones; the t statistics, which indicate the statistical importance of every single variable in the model; and the F statistic which measures the overall effect of the independent variables on the dependent.

Specifically I examined the following model :

$$\Delta P_t=\alpha_0 \quad + \quad \sum_{i=1}^{n} \Delta P_{t-i} \quad + u_t \qquad (2)$$

Where ΔP_t and ΔP_{t-i} are price changes, $\Delta P_t=P_t-P_{t-1}$. Here as in model (1) according to the Efficient Market Hypothesis we should have $\alpha_0 = \alpha_1 = \ldots\ldots\ldots\ldots = \alpha_n = 0$. That is there is no information in past price changes, which can help to predict the current price change.

2.2 Regression Results

In the estimated dynamic regressions, several lagged variables appeared to be statistically significant in explaining the price change at time t. Analytically for the regression of the above type (2) and for a lag length of twenty days, n=20, which represents the period of about a month, the following lagged variables appeared to be statistically significant.

TABLE 2.1

$$\text{Model: } \Delta P_t = \alpha_0 + \sum_{i=1}^{20} \Delta P_{t-i} + u_t$$

Bank of Greece			National Bank			Ergobank		
Lag	Est.	"t"	Lag	Est.	"t"	Lag	Est.	"t"
1	0.11	2.96	1	0.16	3.15	1	0.18	2.85
2	-0.10	2.29	3	-0.17	1.87	8	-0.03	1.69
4	-0.09	2.31	7	-0.06	1.82	9	-0.05	1.42
9	-0.07	2.26	12	0.04	1.92			
17	0.10	3.39	20	0.02	1.95			
19	0.08	2.46						
20	-0.02	2.30						
R^2=0.06 F=2.61			R^2=0.06 F=2.39			R^2=0.05 F=1.47		
$\bar{F}$=4.28 LM(23)=0.75			$\bar{F}$=4.66 LM(23)=0.64			$\bar{F}$=1.95 LM(23)=1.0		
ARCH(23)=4.22			ARCH(23)3.54			ARCH(23)=0.64		

Ionian Bank			Commercial Bank			Piraiki		
Lag	Est.	"t"	Lag	Est.	"t"	Lag	Est.	"t"
1	0.19	4.56	2	-0.10	1.93	1	0.12	2.98
7	-0.06	1.71	3	-0.15	3.21	3	-0.07	1.47
12	-0.06	1.83	4	-0.06	1.67	9	-0.12	2.35
17	0.03	1.75	16	0.07	1.85	17	0.04	1.51
19	0.03	1.44						
R^2=0.05	F=3.07		R^2=0.07	F=1.75		R^2=0.04	F=1.84	
$\bar{F}$=4.40	LM(23)=0.08		$\bar{F}$=4.04	LM(23)=0.08		$\bar{F}$=2.50	LM(23)=0.4	
ARCH(23)=0.29			ARCH(23)=9.69			ARCH(23)=5.41		

Lipasmata			Halkida		
Lag	Est.	"t"	Lag	Est.	"t"
1	0.07	1.66	1	0.11	1.77
2	0.06	1.83	4	-0.14	2.44
12	-0.02	1.65	19	-0.04	1.35
14	-0.04	1.73			
16	-0.03	1.78			
18	-0.04	1.82			
R^2=0.06	F=2.61		R^2=0.06	F=2.39	
$\bar{F}$=4.28	LM(23)=0.75		$\bar{F}$=4.66	LM(23)=0.64	
ARCH(23)=4.22			ARCH(23)3.54		

In the above table only the relatively significant variables are presented, the "t" statistics are in absolute values, the F is the statistic for the F test which tests if a1 = a2 =...a20 = 0, the F bar ($\bar{F}$) refers to the regression with five lags which represents almost a week, ARCH is a test for heteroscedasticity of particular interest for stock prices (large price changes tend to be followed by large price changes), LM is the Lagrange Multiplier statistic testing for autocorrelated error terms. Finally, for the estimation of the above models I used heteroscedastic-consistent covariance martix when it was necessary.

The critical values for the "t" ratios are: 1.96 for 5% significance level, 1.64 for 10% significance level, 1.28 for 20% significance level. For the F test the critical values for twenty and five variables are: 3.02 and 1.88 for 1% significance level, 2.21 and 1.57 for 5% significance level, 1.94 and 1.42 for 10% significance level The critical value for the L.M(23) statistic is 38.08 and for the ARCH(23) test is 1.57.

From the results it is interesting to note that several variables proved to be statistically significant with dominant significant variable the one which refers to the first lag. Another important characteristic of the above regressions is that the first lag is almost always positively related to the dependent variable. The F test in some cases became statistically significant when the lag length was reduced from twenty to five lags indicating the importance of the most recent past values of the dependent variable. Nevertheless, the R^2 as an overall measure of forecastability was small in the estimated models but high in comparison to other studies, Fama (1970).

I should like to note here that in the above model it is expected that some variable will prove statistically significant due to chance; for instance at the 95% confidence interval someone expects one out of twenty variables to be statistically significant by chance. Nevertheless, the uniform statistical significance of the first lag make the above "significant by chance" scenario unlikely at least for the specific first lag.

3. Forecasting Models

Since I have found some statistically significant relationships between price changes it should be reasonable to investigate if there is a statistical model which can explain the price changes better than the Random Walk model on purely statistical grounds.

From the random walk model we can get that $\Delta P_t=u_t$ where u_t is described as white noise (ch 1). The white noise model is an A.R.I.M.A (0,1,0) model. I tried the above form of A.R.I.M.A model for all stocks and I found that the Autocorrelation function of the price changes did not indicate, as expected from the previous results, a white noise process.

I tested the randomness of the price changes through the Box-Ljung statistic. The Box-Ljung (B.L) is a test statistic which tests the null hypotheses that a set of sample autocorrelations is associated to a random series. If a model is fitted well to the data, the residuals should not be correlated, that is the autocorrelations should be small and insignificant. The B.L statistic can be computed at any lag and is assessed against the X^2 distribution with degrees of freedom equal to the particular lag at which the statistic is calculated. The B.L statistic for all the stocks and at every lag was significantly higher than the critical values and the estimated probability for these autocorrelations to be generated by a white noise was calculated to be zero.

Analytically I obtained the following B-L statistics for lags one to ten:

TABLE 2.2

Lag	Bank of Greece	National Bank	Ergo Bank	Ionian Bank
1	17.9	25.3	47.1	50.3
2	26.4	27.2	47.8	52.0
3	38.2	36.1	47.8	52.0
4	51.7	41.6	49.0	54.2
5	52.5	44.6	50.2	54.7
6	52.9	45.6	53.0	58.3
7	53.4	52.7	60.2	65.7
8	55.0	58.4	67.6	65.9
9	57.4	58.4	74.4	66.1
10	63.3	58.7	82.1	66.4

Lag	Commercial Bank	Halkida	Lipasmata	Piraiki
1	9.9	15.0	9.5	24.6
2	21.2	17.2	13.1	24.9
3	54.5	18.8	59.1	30.2
4	64.1	43.9	69.8	30.4
5	66.7	64.3	69.9	34.3
6	66.7	64.4	70.0	35.5
7	67.6	64.9	70.1	35.9
8	76.6	65.3	71.0	36.8
9	76.9	69.2	71.4	53.8
10	84.6	69.2	71.5	58.9

Critical values for lags one to ten.

X^2 .5% :5.0 7.3 9.3 11.1 12.8 14.4 16.0 17.5 19.0 20.4

The next step is to estimate these significant auto correlations and propose a model which describe better the price changes than the white noise process. For the the exploitation of an adequate model which will describe the price changes I followed the Box-Jenkins (1978) technique which is a suggested technique for making short run forecasts. Any model which will be proved to fit the data better than the random walk model following the Box-Jenkins model selection criteria would imply that price changes may be predictable and consequently that the Weak Form of Efficiency may not hold.

3.1 Box-Jenkins Analysis

Box-Jenkins models make no attempt to explain or isolate the economic forces which have generated the data series of interest; the emphasis in Box-Jenkins approach is placed on a rigorous analysis of the statistical properties of the data series. It is via such an analysis that an approximation of the statistical process which generate the data can be derived.

In practice it will often be possible to identify and estimate a number of competing models satisfactorily, all of which will be equally consistent with the data. The basis determinants in such cases is to select the simplest of these models, that is the model with the smaller number of parameters refereed in the Box-Jenkins literature as *the principle of parsimony*.

One assumption of the Box-Jenkins methodology is the assumption of stationarity. By stationarity we mean that the data have a constant mean (there is no trend in the data), a constant variance (homoscedasticity) and stationary covarianve. The reason for requiring stationarity derives from the nature of the Box-Jenkins methodology. The objective of Box-Jenkins anlysisis to identify and estimate a statistical model which can be interpreted as having generated the data. If this estimated model is then to be used for forecasting we must assure that the features of this model are constant through time. For the variable which I am investing, that of price changes (first differences of price levels) following the suggestions of the autocorrelation function and the minimum variance criterion[1], I assumed stationarity, later it will be shown with more sophisticated tests, that this assumption is a valid one.

The first stage of B-J approach is the identification stage. The identification of a model is done through the autocorrelation function (A.F) and the partial autocorrelation function (P.A.F) of the data.

The possible identified model may be:

1) An AR(p) (Autoregressive process of order p) with the general form $Pt= \phi_1 P_{t-1} + \phi_2 P_{t-2} + \ldots\ldots + \phi_p P_p + \varepsilon t$

The autoregressive process is one with a "memory", in the sense that each value is correlated with preceding values.

2) A MA(q) (Moving Average process of order q) with the general form $Pt = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$

In a moving average process, each value is determined by the average of the current disturbance and one or more previous disturbances.

3) A mixed ARMA(p,q) (Autoregressive Moving Average process) with the general form

$$Pt=\phi_1 P_{t-1} + \phi_2 P_{t-2} + \ldots \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \theta_q \varepsilon_q$$

Returning now to the A.F and the P.A.F, the suggestion is that if we observe a geometric decay in the A.F and p significant partial autocorrelations in the P.A.F we have an evidence of an AR(p) process. If there is a geometric decay in the P.A.F and q significant autocorrelations in the autocorrelation function is considered as an evidence of an MA(q) model. Finally a geometric decay in both the

A.C.F and the P.A.F with p and q significant values indicates an ARMA(p,q) model.

The A.F and the P.A.F of price changes were as follows:

TABLE 2.3

	Bank of Greece		National Bank		Ergobank		Ionian Bank	
Lags	A.F	P.A.F	A.F	P.A.F	A.F	P.A.F	A.F	P.A.F
1.	.107	.107	.141	.141	.116	.116	.188	.188
2	-.093	-.105	-.044	-.066	-.002	-.016	.021	-.015
3	-.086	-.065	-.084	-.069	-.001	.001	-.018	-.020
4	-.091	-.085	-.063	-.045	.003	.003	-.031	-.024
5	-.027	-.023	-.046	-.040	-.002	-.003	-.005	.006
6	.008	-.009	-.012	-.012	-.064	-.065	-.057	-.060
7	.009	-.008	-.064	-.075	-.052	-.038	-.081	-.063
8	.046	.036	-.073	-.067	-.032	-.023	-.029	-.003
9	.065	.054	-.016	.022	-.038	-.033	-.004	.001
10	-.054	-.061	-.007	-.034	-.048	-.041	.005	-.059

	Commercial Bank		Halkida		Lipasmata		Piraiki	
Lags	A.F	P.A.F	A.F	P.A.F	A.F	P.A.F	A.F	P.A.F
1	.133	.133	.113	.113	.086	.086	.136	.136
2	-.120	-.140	-.005	-.018	.05	.049	-.023	-.043
3	-.161	-.129	.059	.063	-.199	-.210	-.068	-.060
4	-.108	-.089	-.148	-.164	-.088	-.059	-.011	.006
5	-.012	-.024	-.140	-.105	-.003	.037	-.059	-.003
6	.009	-.032	.006	.026	.017	-.018	-.034	-.022
7	.067	.040	.023	.039	.017	-.016	.020	.025
8	.11	.088	-.03	-.049	.024	.027	-.029	-.046
9	.053	.039	.04	.017	-.023	-.026	-.123	-.119
10	-.06	-.039	.006	-.017	-.008	-.009	-.067	-.038

From the the above we can see that there are significant values in both the Autocorrelation function and the Partial Autocorrelation function since the standard error for these autocorrelations is 0.028 implying that the statistical significance is very strong. The standard error of these autocorrelations is given by the formula $(1/(n-1))^{1/2}$, Fama (1970), where n is the number of the observations. For a large sample as in this case, the standard error becomes very small and so even small autocorrelations can be considered as significant. Nevertheless for the examined data set the autocorrelations were as large as about three and four times the standard error and someone can conclude that these autocorrelations are significant indeed.

The above statistical findings imply that the adequate model which will describe the data may be a kind of AR(p) model, an MA(q) or a mixed ARMA(p,q) model. For every case I tried all the possible suggested models and I chose the one which was more consistent with the B-J model selection criteria.

3.1.1 Box-Jenkins Selection Criteria

The first step in examining the adequacy of any estimated model is to test for the significance of the estimated parameters by looking at their t ratios. If higher order parameters prove to be insignificant then the implication is that the process can be just as adequately described by a lower order process. Thus insignificant parameters would be dropped from the model and the simpler specification then reestimated. Note as the variables in a B-J model do not have a theoretical interpretation there is no need to be concerned with the theoretical relevance of retaining a variable in the model, in B-J only statistical criteria are relevant.

A second criterion of model evaluation is to examine the properties of the residuals of the estimated model. In particular, if the model is correctly specified then by definition the disturbance term ε_t must be random. Therefore we would expect this property of randomness to be reflected in the estimated residuals. One or two high order autocorrelations in the residuals may exceed the 5% significance level by chance but generally, if the *first* and second order autocorrelations are small then probably the model in question is well specified, Pokorny (1980).

Some other model selection criteria which I used are the Akaike Information criterion (A.I.C) and the Schwartz Bayensian criterion (S.B.C). These are statistics which help us to decide the order of a model by taking into account both how the model fits the observed series and the number of parameters used in the fit. We are looking for a model which adequately describes the series and has the minimum A.I.C or S.B.C. Generally speaking the A.I.C criterion is for AR models while S.B.C is more general.

3.2 Box Jenkins Models Results

Using the above criteria and the *parsimony principle* (i.e., to choose the most simple of the adequate models) I concluded that the following models describe better than the White Noise the price changes for the stocks which I am examining.

TABLE 2.4

BANK OF GREECE

MODEL:ARIMA(2,0,1)

$$\Delta P_t = \underset{(6.21)}{0.73}\ \Delta P_{t-1} - \underset{(6.14)}{0.17}\ \Delta P_{t-2} + \underset{(5.29)}{0.63}\ \varepsilon_{t-1} + \varepsilon_t$$

R^2=0.03 S.B.C=10.3 A.I.C=10.3 U=0.81

B.L(1)=0.006 Prob=93%

B.L(2)=0.024 Prob=98%

NATIONAL BANK

MODEL:ARIMA(2,0,1)

$$\Delta P_t = \underset{(12.20)}{0.94}\ \Delta P_{t-1} - \underset{(6.49)}{0.19}\ \Delta P_{t-2} + \underset{(10.71)}{0.80}\ \varepsilon_{t-1} + \varepsilon_t$$

R^2=0.03 S.B.C=9.62 A.I.C=9.63 U=0.77

B.L(1)=0.020 Prob=92%

B.L(2)=0.170 Prob=91%

ERGOBANK

MODEL:ARIMA(1,0,0)

$$\Delta P_t = \underset{(3.92)}{0.11}\ \Delta P_{t-1} + \varepsilon$$

R^2=0.01 S.B.C=7.47 A.I.C=7.46 U=0.92

B.L(1)=0.004 Prob=94%

B.L(2)=0.281 Prob=86%

IONIAN BANK

MODEL:ARIMA(1,0,0)

$$\Delta P_t = 0.18\ \Delta P_{t-1} + \varepsilon_t$$
$$(6.50)$$

R^2=0.03 S.B.C=7.67 A.I.C=7.67 U=0.79

B.L(1)=0.008 Prob=92%

B.L(2)=0.117 Prob=94%

COMMERCIAL BANK

MODEL:(2,0,0)

$$\Delta P_t = 0.15\ \Delta P_{t-1} - 0.13\ \Delta P_{t-2} + \varepsilon_t$$
$$(5.20) \qquad (4.74)$$

R^2=0.03 S.B.C=5.95 A.I.C=5.94 U=0.67

B.L(1)=0.372 Prob=54%

B.L(2)=0.396 Prob=82%

LIPASMATA

MODEL:(1,0,0)

$$\Delta P_t = 0.08\ \Delta P_{t-1} + \varepsilon_t$$
$$(2.94)$$

R^2=0.007 S.B.C=7.86 A.I.C=7.85 U=0.76

B.L(1)=0.020 Prob=88%

B.L(2)=5.190 Prob=7%

HALKIDA

MODEL:(1,0,0)

$$\Delta P_t = 0.11\ \Delta P_{t-1} + \varepsilon_t$$
$$(3.93)$$

R^2=0.01 S.B.C=2.34 A.I.C=2.33 U=0.74

B.L(1)=0.001 Prob=97%

B.L(2)=0.581 Prob=74%

PIRAIKI

MODEL: (1,0,0)

$$\Delta P_t = \underset{(4.75)}{0.13}\, \Delta P_{t-1} + \varepsilon_t$$

R^2=0.01 S.B.C=5.64 A.I.C=5.63 U=0.74

$B.L_{(1)}$=0.04 Prob=84%

$B.L_{(2)}$=1.35 Prob=51%

Where AIC is the Akaike criterion, SBC the Schwart Bayensian criterion, $B.L_{(i)}$ the Box-Ljong test for autocorrelation at lag i and Prob. the probability that this autocorrelation is generated by a white noise. Finally U is the Theil's inequality coefficient for an out of the estimation period of almost five months.. For the perfect forecast U=0, for the naive static forecast which the E.M.H implies U=1. In the above models U is less than one in all cases, indicating that the estimated ARIMA models are better forecasting models than the Martingale model which implies E $\Delta P_t/I_{t-1}$)=0

I should like to note here that for the estimation of the A.F, P.A.F and models I excluded the last five months of the daily observations in order to test later with a trading rule the prediction validity of the models in an out of the sample period.

From the above results we can conclude that in all cases there is a model which explains the price changes better than the model which claims that the price changes are random. Nevertheless B-J is an approach which we use to make only short run predictions. The estimated models are based on the first few autocorrelations and partial autocorrelations of the price changes. Price changes though may follow some kind of long run periodicities which are not captured in the above models. In order to investigate the existence of such long run cycles I used the technique which is called Spectral Analysis.

4. Spectral Analysis of Price Changes

Spectral analysis is about rhythms. It is used to exploit various kinds of periodic behaviour in series, although it can be used for non periodic data. A Spectral analysis of a series yields a description of that series in terms of cycles of different period (length) or frequency that generates the series. This is portrayed in a graph called *a periodogram* which shows an estimate of the amount of variance of the series accounted for by cycles of each frequency. Although Spectral descriptions are given in terms of frequencies or periods of the component cycles there is an exact relationship between the frequency representation and the autocorrelations of the series.

Spectral analysis is almost model free. It analyses series in terms of sine and cosine waves , but this analysis is purely mathematical and it is not based on any theory about the process underlying the series. In contrast to other time series techniques we do not determine a parametric model of our data and then estimate it. Instead we estimate the spectrum without any a priori constraints. As a sequence of this Spectral methods are not worth doing if we only had a small amount of data because a small series has so little information that we can not analyze it without a model. Spectral analysis is usually done with hundreds of observations.

In order to model cycles of different length, we express the series in terms of sine and cosine functions having different frequencies. The actual frequencies are chosen so that the length of the series contains a whole number of cycles at each frequency. These are called Fourier Frequencies . In general the J^{th} Fourier frequency is expressed as:

$$\text{Frequency } J = \frac{j}{N},$$

where the j is the number of times the cycle repeats in the sample and N is the number of observations. The Fourier frequencies are important to explain the periodogram which is a two axis graph where the horizontal axis shows the frequencies into which Spectrum has decomposed the series and the vertical axis which shows the relative weight or importance of each frequency. The periodogram of a series shows the energy or variance at each of the Fourier frequencies.

In the periodogram we can observe several peaks which denote some kind of cycle. It would be unwise though to attribute significance to each individual peak. However we can apply various smoothing transformations to the periodogram terms and reduce their variance. Smoothing transformations of a periodogram are called "windows". We define a window by choosing the shape and the number of terms (span) of the group of neighboring points that are to be averaged together.

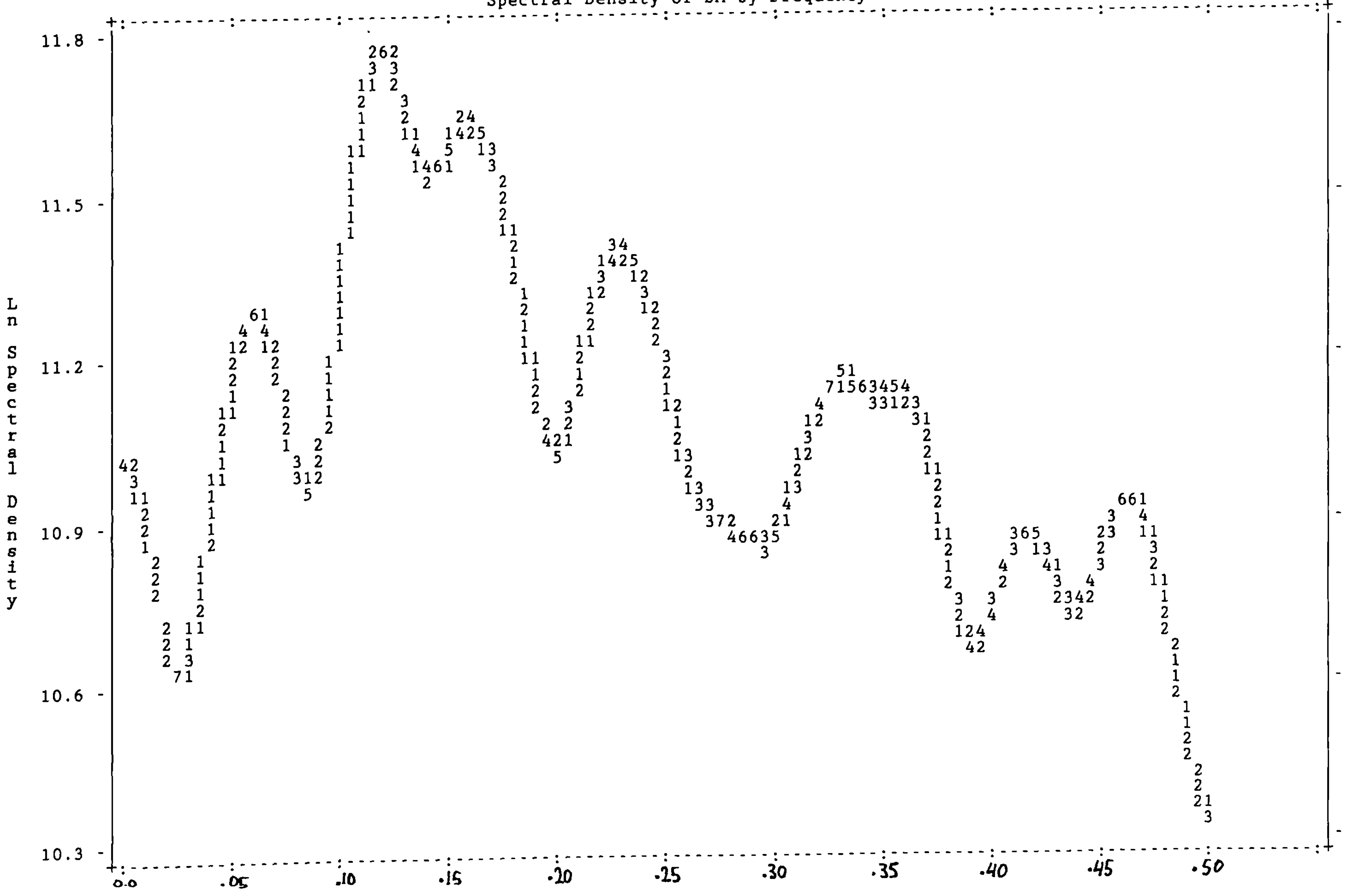
The smoothed periodogram is called Spectral density estimate. A wide data window reduces the effect of random variation in the periodogram and makes the spectrum density plot easier to read but also introduce some bias if someone smooths the periodogram too much. In this case (more smoothing than required) we may miss spikes corresponding to important periodic variation at particular narrow frequency ranges. One rule of thumb is to make the data window 5% to 10% of the number of observations. In the spectral analysis I used 1240 observations of price changes which contain the two days cycle at frequency 0.5, a weekly cycle at frequency 0.2, a monthly cycle at frequency 0.05 and an annual cycle at frequency 0.004 (all the above cycles repeat in the number of observations I used the two days cycle repeats 640 times, the weekly cycle repeats 248 times, the monthly 62 times and the annual almost 5 times). The window I used was Hamming type with a span of 63 (5% of the observations) If price changes were a white noise process as the Efficient Market Hypotheses predicts we should not observe any cycles at all because the White noise is the smoothest possible series and varies only at frequency zero while a White noise with a mean of zero will have no spikes at all.

4.1 Spectral Analysis Results

For Hamming window and a span of 63 I obtained the following periodograms.

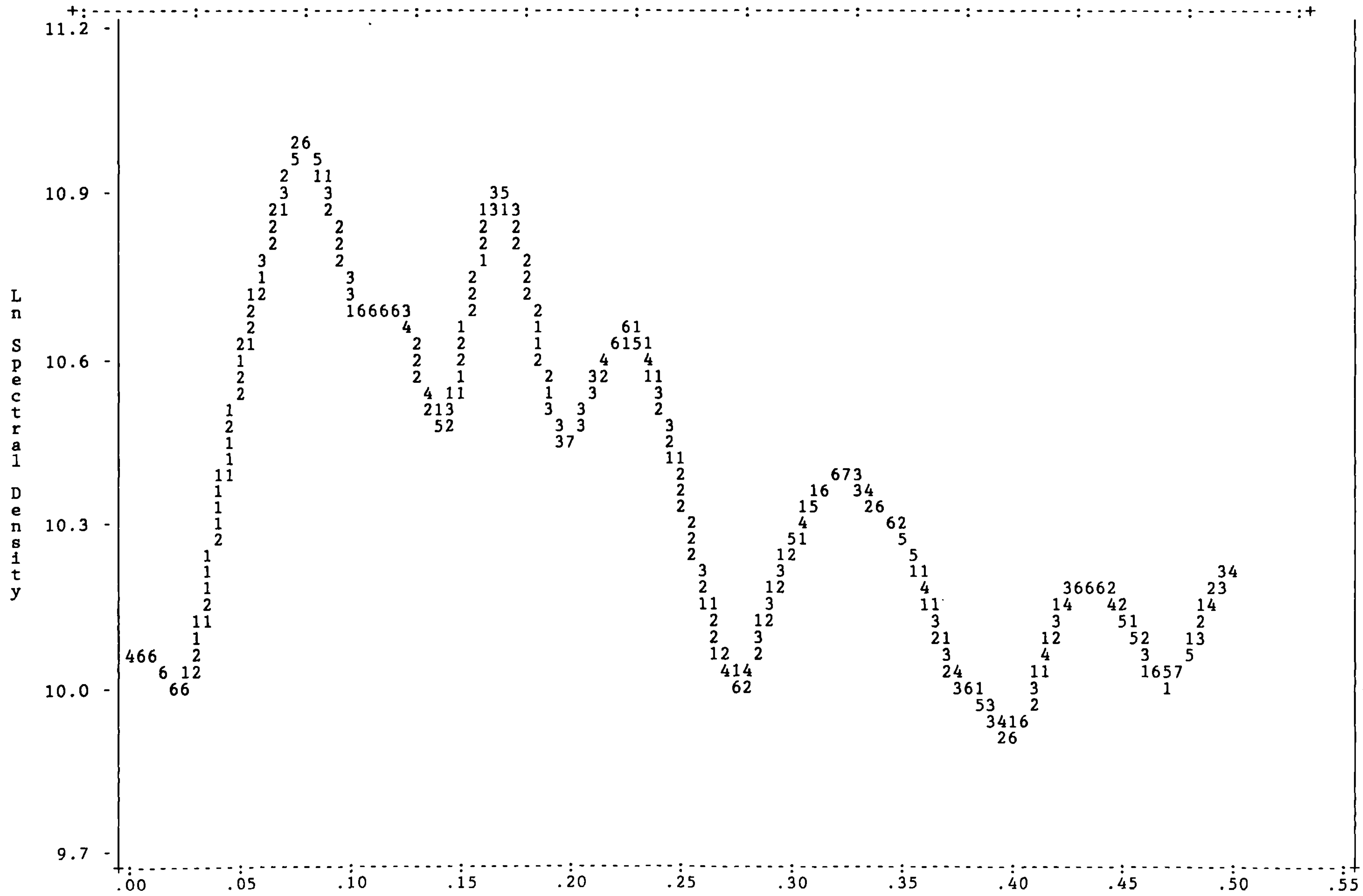
Bank of Greece

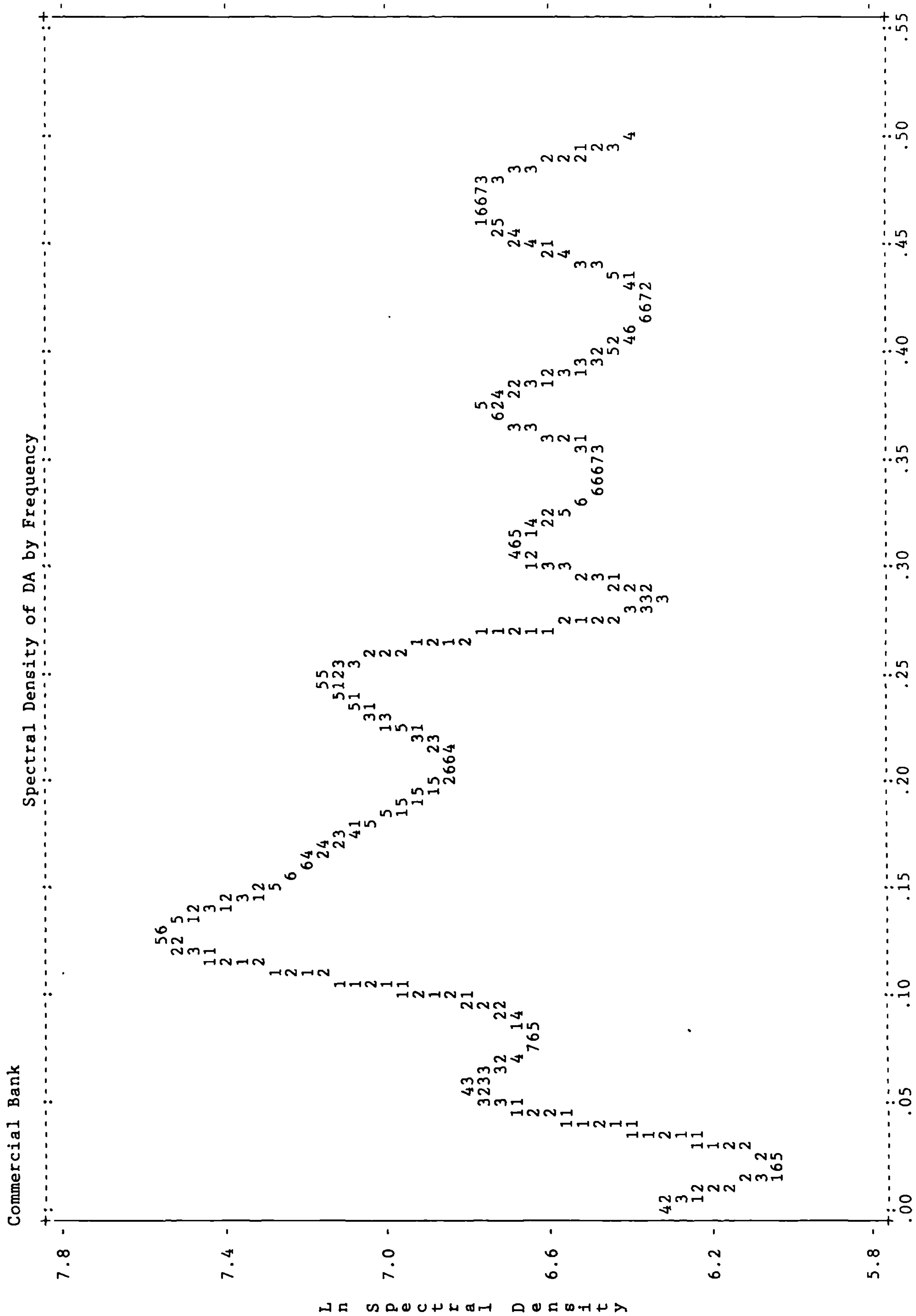
Spectral Density of DA by Frequency

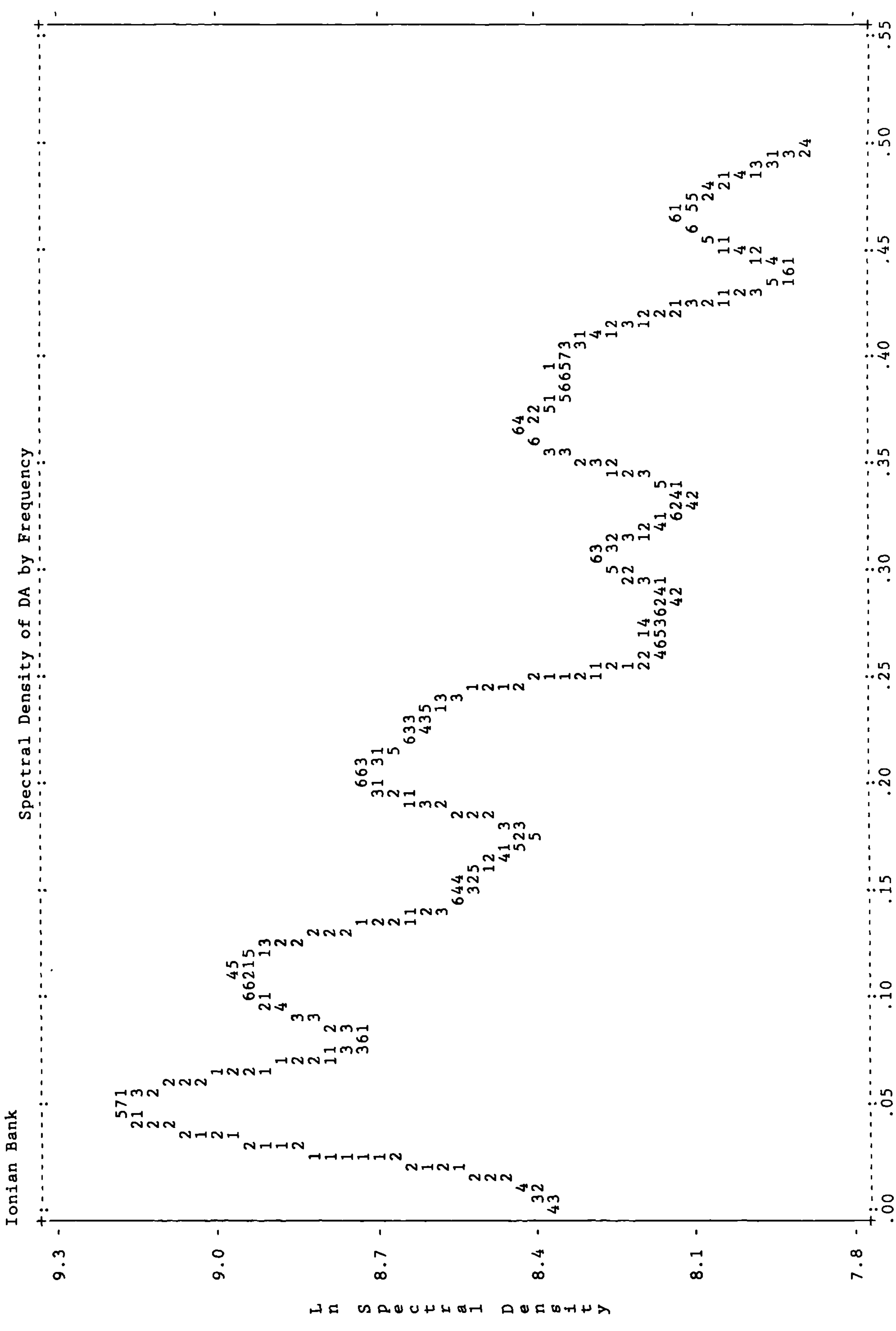


Spectral Density of DA by Frequency

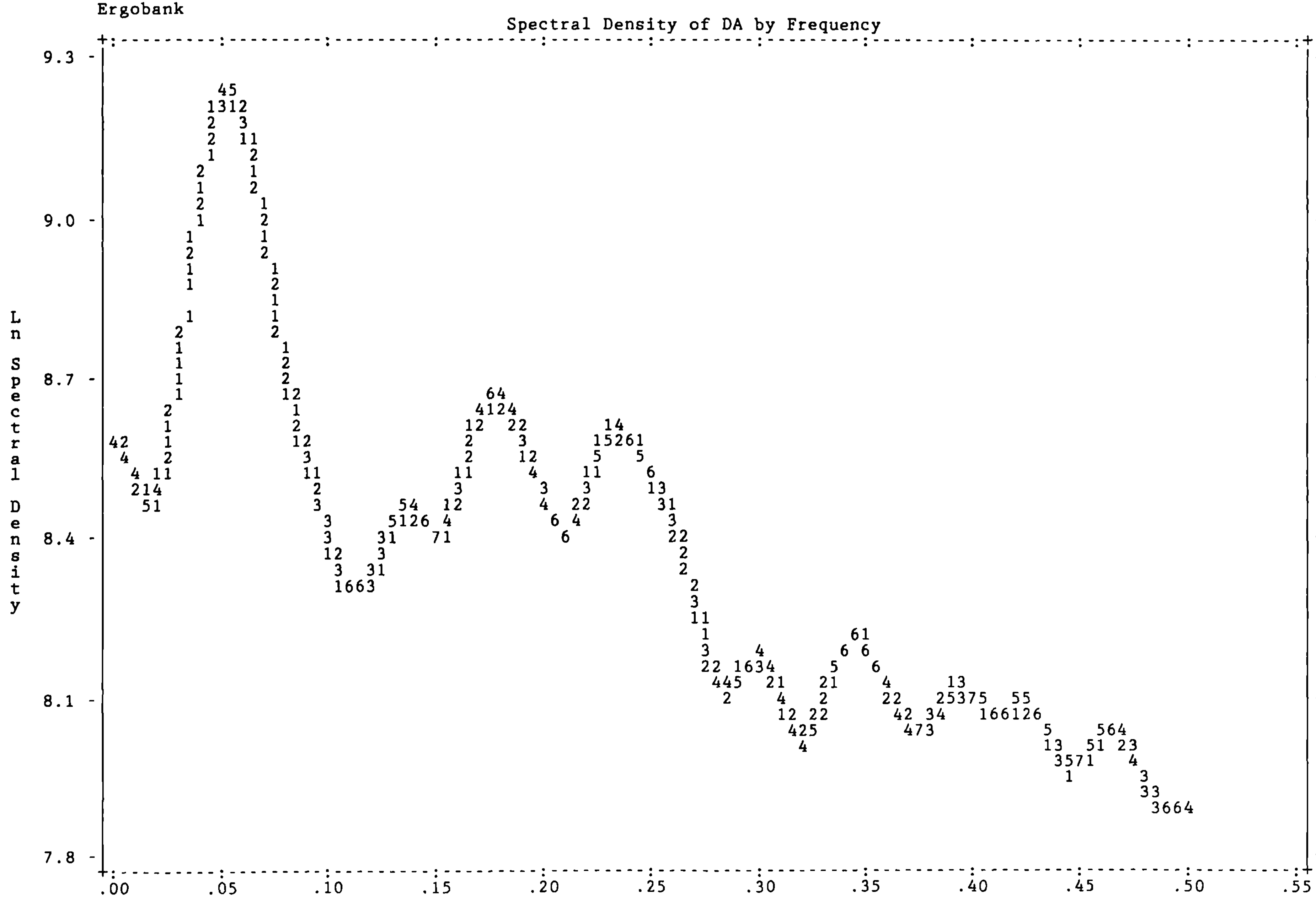
National Bank




Commercial Bank
Spectral Density of DA by Frequency
Ln Spectral Density
7.8
7.4
7.0
6.6
6.2
5.8
.00
.05
.10
.15
.20
.25
.30
.35
.40
.45
.50
.55

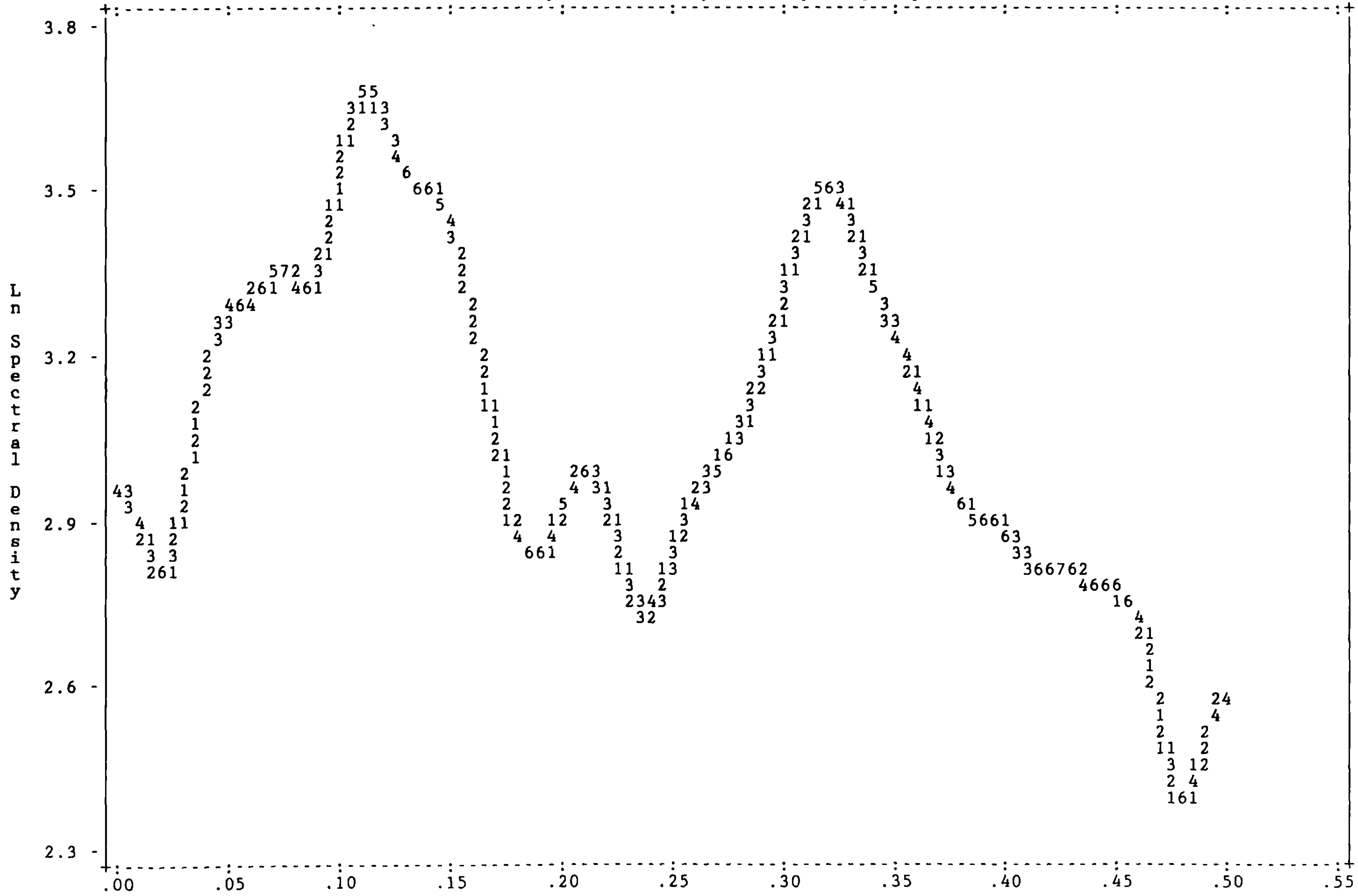

Ionian Bank
Spectral Density of DA by Frequency
Ln Spectral Density
9.3
9.0
8.7
8.4
8.1
7.8
.00
.05
.10
.15
.20
.25
.30
.35
.40
.45
.50
.55

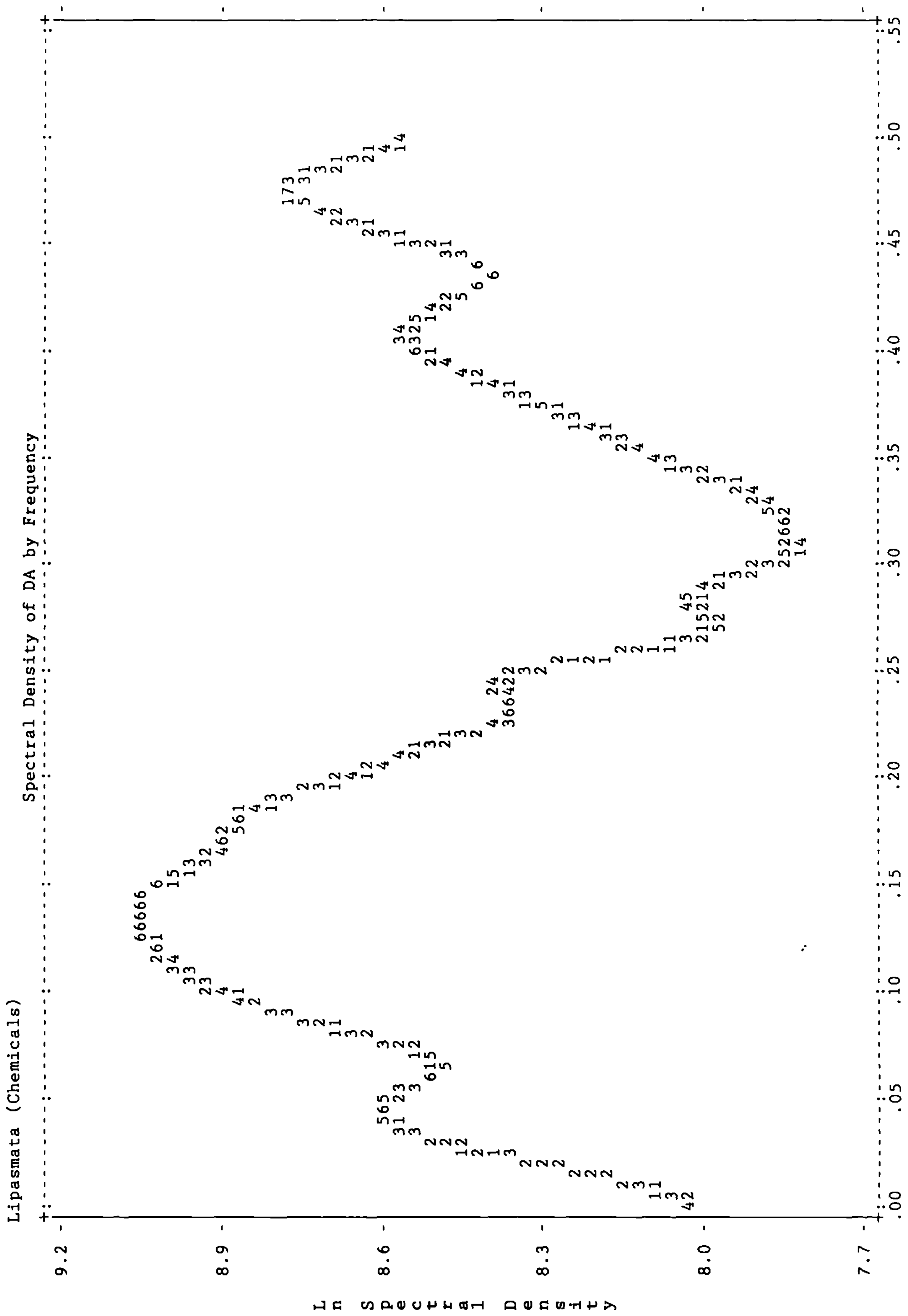
Ergobank

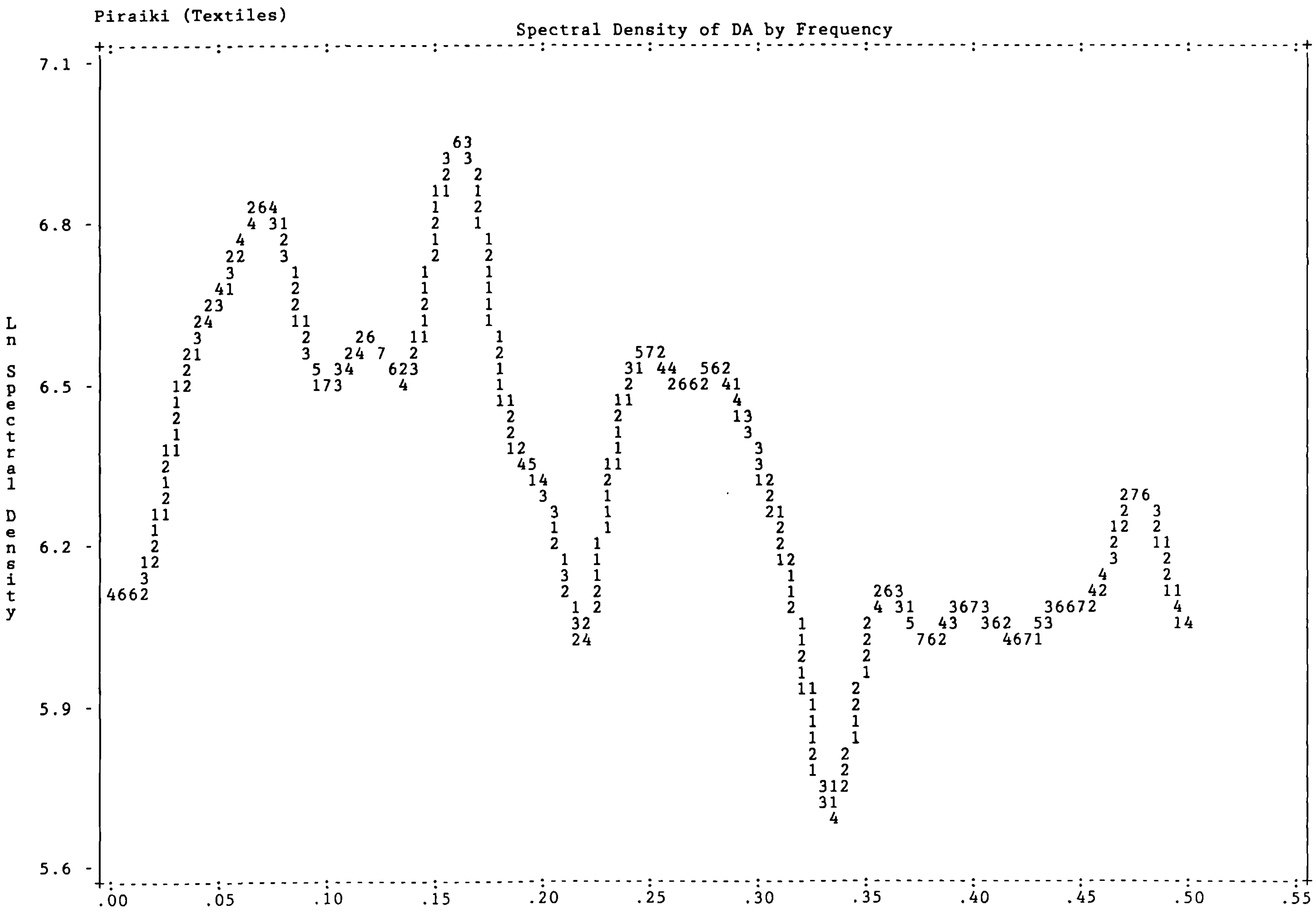

Spectral Density of DA by Frequency
Ln Spectral Density
9.3
9.0
8.7
8.4
8.1
7.8
.00
.05
.10
.15
.20
.25
.30
.35
.40
.45
.50
.55

Halkida (Cements)

Spectral Density of DA by Frequency




Lipasmata (Chemicals)
Spectral Density of DA by Frequency
Ln Spectral Density
9.2
8.9
8.6
8.3
8.0
7.7
.00
.05
.10
.15
.20
.25
.30
.35
.40
.45
.50
.55



Piraiki (Textiles)
Spectral Density of DA by Frequency
Ln Spectral Density
7.1
6.8
6.5
6.2
5.9
5.6
.00
.05
.10
.15
.20
.25
.30
.35
.40
.45
.50
.55

The most important result from the periodograms is that the examined series of price changes are definitely not a white noise process. In all cases the periodograms exhibited strong variation at several frequencies while for the case of a white noise process we should expect an almost flat periodogram.

The second important characteristic of the examined periodograms is that they show, more or less, high variation at low frequencies and lower variation at higher frequencies. This kind of periodogram is characteristic for A.R process with positive coefficient. This result comes to verify the results of the rationality tests and the Box-Jenkins models which indicated the positive dependence of successive price changes.

A third result from the periodograms is that they show cycles at or near the frequencies 0.05 and 0.20 which represent the monthly and the weekly cycles. I must note here that from the periodograms I expect to observe some leakage as described before.

Again, the conclusion from the Spectral Analysis is that price changes in the Athens Stock Exchange are not independent as the Efficient market Hypothesis predicts. The observed cycles imply that the Greek investors have not identify them, because if they had so, they would eliminate them. The "causes" of the observed weekly and monthly cycles of are not easy to be specified. For the weekly cycle it can be a Monday or some other day of the week effect. It would be very easy to test such an explanation by regressing the price change at time t on five dummy variables which would represent the five days of the week which the Athens Stock Exchange is open. Nevertheless, the results would not be indicative since for the very few days where the Athens stock Exchange was closed as mentioned in the beginning of the chapter ruin the day of the week sequence of the data. The same applies to the monthly cycle since it is not clear which day of the month the twenty days cycle indicates.

5. Commenting on the results

The prominent result of the statistical analysis described in this chapter is that in the Athens Stock Exchange and for the examined stocks successive price changes are positively and strongly correlated. Some other studies (ch 1) which report evidence of a positive relationship between successive price changes attribute this result mainly to the non-frequent trading of the examined securities or the practices of the Stock Exchange in question.

From the operations and practices of the Athens Stock Exchange[2], it does not seem to be any possible source of the pattern discovered in this study. Additionally the examined stocks are among the most active in the Athens Stock Exchange and the prices used for the statistical analysis are prices at which trade has taken place.

One possible interpretation of the statistical results is that the Greek Stock Market reflects slowly the news on the examined stocks. This case implies market inefficiency if someone based on the pattern which is created by the slow reflection of news on the securities make above normal profits. On the other hand if the pattern is unprofitable the Efficient market Hypothesis will be supported since there are no incentives for the competing investors to take advantage of this pattern and eliminate it.

Some researchers, Gowland and Baker (1976) and Goodhart and Smith (1985) noted the importance of introducing some sort of time element into the Efficient Market Hypothesis. "*Markets do not or can rather not be expected to react instantaneously, and one might therefore expect that the shorter the observation period the more likely there is to be evidence of inefficiency*" and that "*evidence of inefficiency may appear given that there are costs of adjustment and comparative advantage in processing data*", Gowland (1986).

The Efficient market theory assumes that information is costlessly available to all market participants. In the real world though, information is not costless. For someone to be well informed requires time and money to be spend on it. For instance Technical and Fundamental analysis require specialists, probably well paid, also require expensive advanced technology. Even for someone who can not afford to employ specialists and machines, it is required a great amount of time devoted in selecting and processing information, which in fact is an opportunity cost. The investors who can not afford the cost of gathering and processing information arevery likely to develop a strategy based on readily available and thus cheap "information", like the past price changes. Such an explanation would be consistent with the findings from the empirical analysis.

When information comes in the market it is embodied in prices by the investors who are able to acquire it. Investors who can not afford the cost of information may treat the price change at time t as valid information, "signal", for the next price change, and trade based on this signal.

Thus it is possible that:

$\Delta P_t^* = \alpha \Delta P_{t-1}$ where a>0 and star denotes expectation.

The above model implies that if a stock price has risen investors expect that it will continue to rise i.e., investors believe that there are trends in price changes. This is because the information set of this kind of investors may be:

$$I_t = \{\Delta P_{t-i}\} \quad i=1 \quad n.$$

From the statistical results it seems that if this is the case, these investors overweight the "information" ΔP_{t-1} and trade on that "information" i.e., they may buy after a price increase and sell after a price decrease because *"Res tantum valet quanto vendi potest"* (Something is worth what someone is willing to pay for it).

In the above Bandwagon expectations model, Frankel and Froot (1977), Maddala (1989), the variable ΔP_t^* is not directly observable and direct tests to see if $\Delta P_t^* = \alpha\ \Delta P_{t-1}$ are not easy to apply. Nevertheless, such a model is more likely to fit the statistical results than the static expectations model $P_t^{*}=P_{t-1}$ which the Efficient Market Hypothesis and the martingale model predict.

6. Is the Greek Stock Market Inefficient?

All the above Technical analysis suggests that in the Athens Stock Exchange there are some regularities in price movements. If we try to summarize our results we could point out the following :

1) Price changes are not random. From the autocorrelation function of price changes and the autoregressive models it seems that the price change of a stock at day t-1 has some statistical power in explaining the price change at day t. Some price changes at days prior to t-1 appear to be significant in explain the change at time t. The conventional F tests indicated that the recent price changes, those within a period of five days have stronger predictive value than those of distant days.

2) Box-Jenkins model building method indicated that there are models other than the white noise which can explain price changes.

3) Spectral analysis of the price changes verified the above relationships of successive price changes but also Spectral Analysis indicated some other lower frequents (longer cycles) to be important ones as well.

Do all the above statistical results indicate that the Greek Stock Market is not an efficient one?

The answer to such question is that the above statistical relationships would indicate market inefficiency if someone could use them to predict price changes better than the other market participants, and profit from these predictions. The statistical results indicate that someone can predict the price changes better than the market because if the market had used the significant explanatory variables for predictive purposes the significant explanatory variables should not be proved significant. Not all the times such statistical relationships indicate a market inefficiency. There may be cases where serial correlation appears to be unprofitable in practice.

In order to test the efficiency of the market we will try to see if a trading strategy based on the above statistical results is a better strategy compared with the the simple buy and hold strategy (test for the Submartingale model). When forming the trading rule which will be compared with the Buy and Hold it is suggested to take into account the following factors:

1) Brokerage costs. These costs involve the costs of data search, model building and model operation. These costs are difficult to estimate and may be different for different agents. Nevertheless, in the beginning of this chapter I assumed that the data which I will use throughout this study is considered to be free and readily available information in the sense that anyone can acquire them without paying any special price. An important cost, though, that someone has to take into account when testing the trading rule is the cost which is paid to the stockbroker when a transaction takes place.[3] Thus, when I will test the trading rule I will take into account these

costs.

2) Tests out of the sample In order to avoid the possibility for an ex post selection bias in the sense that a profitable trading rule applies to one particular period and fail outside the sample period one must ensure that the trading rule performs well out of the sample. This can be done by estimating a model for a period t to t+n and test the prediction validity of the model for the period t+n+1 and afterwards. In addition one can test the prediction validity of the model out of the sample period by using the prediction failure tests from the Econometrics literature. If a model performs well in the period t to t+n, and passes the prediction failure test for the period after t+n, than one can assume that the model performs well out of the sample data set.

3) Risk adjustments In the case when someone is testing alternative portfolios he should allow for risk adjustments because a higher risk portfolio is expected to earn a higher return than a low risk portfolio. This can lead to the false result that the proposed trading rule performs better than the Buy and Hold strategy when the trading rule is based on a risky portfolio. Such adjustments are necessary under the assumption of risk aversion. Under the assumption of risk neutrality which is implied by the fair game model one should choose the portfolio with the higher return. Also risk adjustments are not necessary when someone compares the profits/losses of the same stock under different trading strategies.

From the statistical results, as repeatedly stated before, successive price changes are positively and strongly related in the Athens Stock Exchange. A positive price change is likely to be followed by a positive and a negative by a negative. On the contrary the Efficient Market Hypothesis assumes that price changes are independent and the chance of a positive change to be followed by a positive are on average only fifty per cent.

More information in the above finding is added by the Box-Jenkins models when the suggested model is an ARMA or an AR higher than AR(1). Thus the trading strategy will be based on the Box-Jenkins models. When, according to the Box-Jenkins models, I forecast a positive change I can buy at the time of the prediction and when I forecast a negative change to sell at the time of prediction. This strategy is characterised by the frequent trading and the high transaction costs which occur every time trade takes place. Thus I can restrict the above strategy as follows:

If $F(\Delta P_t)>0$ and $F(\Delta P_t)$ > Brokerage cost per share then Buy stock

If $F(\Delta P_t)<0$ and $|F(\Delta P_t)|$ > Brokerage cost per share then Sell stock and Hold Cash

The above trading rule says that if the forecast price change $F(\Delta P_t)$ is positive but also the forecasted rise in price is higher than the transaction costs per share which will be paid when the transaction takes place then the forecasted net profit is positive and someone buys the stock. By the same token when the forecasted drop in price in absolute value is higher than the transaction cost per share someone should sell the stock and hold cash. The transaction costs are the official brokerage costs of the Athens Stock Exchange and vary from 0.5% to 1% according to the amount of money invested. In the beginning of my trading strategy I assumed that the amount of money invested is 5 million Dracmaes with a brokerage cost of 0.5% since I believe that this amount of money represents the average investment in the A.S.E. then the transaction cost varies according to the fluctuations of capital invested.

The above strategy when simulated for an out of the estimation period of almost five months on a daily basis, indicated that the trading strategy based on the ARIMA forecasts outperformed the Buy and Hold strategy in all cases except the case of ERGOBANK.

TABLE 2.5

Trading rule results based
on forecasts from ARIMA models
(in Wealth units)

	Bank of Greece		National Bank		Ionian Bank	
Day	B & H	T/R	B & H	T/R	B & H	T/R
1	100	100	100	100	100	100
10	95	100	90	100	99	104
20	110	107	102	108	105	106
30	111	113	104	115	111	116
40	109	113	114	125	111	116
50	109	121	118	137	122	126
60	109	120	110	136	127	136
70	109	123	114	147	136	147
80	110	123	115	149	140	151
90	108	123	113	146	134	148
100	108	123	114	147	138	148

	Commercial Bank		Ergobank		Piraiki	
Day	B & H	T/R	B & H	T/R	B & H	T/R
1	100	100	100	100	100	100
10	93	105	101	100	152	152
20	95	110	111	100	152	163
30	98	117	109	100	137	177
40	95	118	110	100	117	176
50	101	112	116	100	58	176
60	95	127	120	99	76	244
70	98	139	128	105	55	244
80	98	145	152	125	76	333
90	95	141	139	121	70	407
100	96	143	138	120	99	574

	Halkida		Lipasmata	
Day	B & H	T/R	B & H	T/R
1	100	100	100	100
10	103	148	108	111
20	108	149	103	114
30	132	173	98	113
40	137	178	95	113
50	155	204	89	113
60	130	196	87	113
70	133	196	90	113
80	164	231	90	113
90	159	258	90	113
100	164	266	93	113

Wealth units are money units and they have as base the day one where an investor has the same wealth under both strategies. Note than in the case of the Ergobank where the Buy and Hold outperformed the trading rule the Theil's inequality coefficient was higher in comparison to the other cases and very close to unity which represents the static forecast in an efficient market.

The above results indicate that for the examined stocks, except one, the Greek stock market is an inefficient market since the statistical results which contradict the Efficient Market Hypothesis proved to be profitable in practice.

7. Tests for Predictive Interrelationships Between Stocks in the Athens Stock Exchange

In the previous chapter, by examining the Weak Form of the Efficient Market Hypothesis, it was discovered that in the price series of the examined stocks there was information which hadnot been utilised by market participants,and consequently could help to predict profitably stock price changes; i.e., the information set $I_{t-1}=[\Delta P_{j,t-1}]$ was useful in forecasting the price changes of a stock j. In this section I will investigate if there is information in the price series of one stock which is useful in forecasting the price behaviour of another stock i.e., the information set in question for a stock j will be $I_{t-1}=[\Delta P_{i,t-1}]$, where i a stock different than stock j.

It is necessary at this stage to define which of Fama's forms of Efficient Markets our investigation will examine. According to Fama in the Weak Form of Efficiency *"..the information subset of interest is just past price (or return) histories"*, for the Semistrong Form *"...the concern is the speed of adjustment to other obviously publicly available information (e.g announcements of stock splits, annual reports, new security issues e.t.c)"*, Fama (1970).

Nevertheless, many authors argued that the above definitions are not very strict; *"Clear cut distinctions do not exist among these categories."*, Foster (1986). Whether the above test is a test for Weak or Semistrong Form of

Efficiency depends on how one interprets Fama's words "*past price histories*". If past price histories concern only the price histories of the stock in question then the test which I will perform is a test for the Semistrong Form of Efficiency, but if it refers to all stocks price histories then the proposed test is a test for the Weak Form.

Fama's information set in his definition for the Semistrong form does not include, and I think does not imply, past prices of other stocks. This, in addition to the structure of the tests I will use, which include both lagged dependent and explanatory variables lead me to the view that the tests which will follow are tests for a wider but Weak Form of Market Efficiency.

The examined stocks, for the empirical analysis which will follow are the same as in the previous chapter and the examined time period is again from 1982 to 1986, on the basis of daily closing prices.

7.1 Econometric Tests for Predictability

7.2 Granger Causality Tests

A very popular way to test if there is any temporal statistical relationship with predictive value between two time series is the Granger causality test, Granger (1969). Granger in order to explain the notion of causality, often referred as to Granger-Wiener causality in recognition of the earlier work of Wiener (1956), starts from the premise that the future can not cause the present or the past. If an event A occurs after an event B, we know that A can not cause B. At the same time if A occurs before B it does not necessarily imply that A causes B.

Nevertheless, the term causality is unfortunate; for instance the weather forecast occurs before the weather but obviously does not cause the weather. Thus, when we test for causality, in fact we test for precedence and particularly for linear precedence, so in practice if we observe Y_t and X_t as time series we would like to know whether Y_t precedes X_t, X_t precedes Y_t, they are contemporaneous, or they are not temporally related.

Granger definition of causality is in terms of predictability : "*A variable X causes another variable Y with respect to a given information set that includes X and Y, if present Y can be better predicted by using past values of X than by not doing so* ". Granger's tests for causality, in the sense of precedence, are based on the following statistical reasoning : If we consider two time series as Y_t and X_t, the series X_t fails to Granger cause Y_t if in a regression of Y_t on lagged Y's and lagged X's the coefficients of the latter are zero.
That is consider equations (1) and (2):

$$Y_t = \alpha + \sum_{i=1}^{k} \beta_i Y_{t-i} + \sum_{i=1}^{K} \gamma_i X_{t-i} + \varepsilon_t \qquad (1)$$

$$X_t = a + \sum_{i=1}^{k} \delta_i X_{t-i} + \sum_{i=1}^{k} \zeta_i Y_{t-i} + v_t \qquad (2)$$

If, in the above equations, with an F test $\gamma_i=0$ for i=1,2,3....k in (1) we can conclude that X_t fails to Granger cause Y_t. If also $\zeta_i=0$ for i=1,2,3...k in (2) then Y_t fails to Granger cause X_t. Then we can conclude that the two series are temporally unrelated. If $\gamma_i\neq0$ for i=1,2,3....k in (1) and $\zeta_i=0$ for i=1,2,3....k) in (2) then X_t Granger cause Y_t. Also if $\gamma_i=0$ (i=1,2,3...k) in (1) and $\zeta_i\neq0$ (i=1,2,3....k) in (2) then Y_t Granger cause X_t. Finally, if γ_i and ζ_i are different from zero in (1) and (2), then we conclude that between X_t and Y_t there is a bidirectional causality in the sense that X_t Granger cause Y_t and Y_t Granger cause X_t. In all the above regressions the error terms ε_t and v_t should be white noise and ε_t and v_t should not be correlated at any lag other that t.

If in the above regressions (1) and (2) we also include the current value of the explanatory variable then we test for instantaneous causality, and equations (1) and (2) become:

$$Y_t=\alpha + \sum_{i=1}^{k} \beta_i \, Y_{t-i} + \sum_{i=0}^{k} \gamma_i \, X_{t-i} + \varepsilon_t \qquad (3)$$

$$X_t= a + \sum_{i=1}^{k} \delta_i \, X_{t-i} + \sum_{i=0}^{k} \zeta_i \, Y_{t-i} + v_t \qquad (4)$$

The test procedure for equations (3) and (4) is as described before, but we test if $\gamma_i=0$ for (i=0,1,2,,,k) and $\zeta_i=0$ for (i=0,1,2,3....k). For the statistical validity of the above test it is also necessary that the error terms

ε_t, v_t should not be correlated at any lag.

The Granger causality test enable us to make predictions in terms of linear precedence and since prediction is a very important element when someone tests the Efficient Market Hypothesis, the Granger Causality tests appear to be very useful. Nevertheless, it must be remembered that not all Granger causality results imply market inefficiency. For the case where two time series which represent price changes are found to be temporally unrelated; i.e., there is no Granger causality between them, then the evidence in favour of Market Efficiency is straightforward. In addition I believe that the concept of Market Efficiency can not be evaluated in two other cases.

The first case is when there is an instantaneous Granger causality between Y_t and X_t. Such a causality is expected under the Efficient Market Hypothesis. According to the Efficient Market Hypothesis prices react to the current news; thus when we include in models (3) and (4) as an explanatory variable for the price change of stock X or Y at time t, the contemporaneous price change of stock Y or X, in fact we test for the reaction of stocks X and Y to the current news since the price change of a stock at time t proxies for the news at time t. Thus, the structure of the test for instantaneous Granger causality is such that it does not provide evidence to evaluate the Efficient Market Hypothesis.

The second case is where there is a bidirectional Granger causality. For this kind of causality, as already known, both γ_i and ζ_i in equations (1) and (2) are different from zero for i=1,2,3....k. This kind of causality implies that Y_t precedes X_t at some point in time but in the same fashion at some other point in time X_t precedes Y_t. In this case there is a feedback between the series Y_t and X_t and there is not a clear relationship between them in terms of predictability, Morkerjee (1987).

In recent years, apart from the Granger test an array of causality tests has been suggested which can be viewed as variations of the original test proposed by Granger. Among the most popular are those proposed by Sims (1972) and Pearce (1977), however I prefer the original Granger test because the structure of this test enables us to draw causality inferences only from past values of the explanatory variable and thus I consider it as direct test for market efficiency.

Although Granger tests can be proved useful when someone tests the Efficient Market Hypothesis, it has been persuasively argued that these tests are an illustration of soft rather than hard econometrics, owing to the number of supplemental assumptions that must be made regarding, for example, normality, lag specification, omitted variables, and autocorrelation, in order for the calculated F statistics to serve as a valid basis for determining whether coefficients are significant. "*We are left with an awkward situation in which the test for causality seems so easy to undertake, provided one closes one's eyes to the inherent softness in each step of the development and provided the significance of the results are agreeable to the researcher*", Rowley and Jain, (1986).

The arbitrary specification of the lag length is referred as one important drawback of the test. For instance a researcher can progressively reduce the lags of the explanatory variables and obtain probably different F statistics. Econometric practice suggests that the lagged variables should be in accordance with the data time interval and the economic theory i.e for the case of monthly data, twelve lags seem to be the appropriate lag length. The above suggestion in econometric terms, is in order to avoid any problems of autocorrelation due to misspecified dynamics or seasonal effects. But what one can say about the lag length in the case of daily data or the case of stock prices which the theory predicts that they are not correlated, so they may not create any autocorrelation problem. Thus, in the absence of autocorrelation the lag length is entirely arbitrary. In such a case, k lags may not indicate a Granger causality but $k \pm q$ lags may indicate a Granger causality.

From my point of view, another weakness of the Granger causality test is the specification of the test. In econometric theory it is argued that variables with absolute t ratios greater than one add to the explanatory power of the model. Nevertheless, it is possible in a Granger test to observe t ratios greater than one, even some greater than the 5% critical value, but the F test be less than the critical value which suggests causality. In such a case someone has to conclude that there is not any Granger causality between the examined variables. It seems that we may loose the tree (the individual lag), because we are looking the forest, (the whole of the lags), and when testing the Efficient Market Hypothesis the "tree" may be of great importance.

Finally, a drawback associated with the Granger causality test is that it does not utilize all the information contained in the data in order to draw causal conclusions, Maddala (1988), and this is because the usual practice for the above described Granger causality test is to use stationary data.

The notion of stationarity was introduced in the previous chapter in Box-Jenkins models. Stationarity requires that the processes in question to be in a particular state of statistical equilibrium, Box and Jenkins (1976). A stochastic process is said to be stationary if its properties are unaffected by a change of the time origin; thus for the process X_t its mean, variance and covariance should be constant over time i.e.,

$$E(X_t)=\mu$$

$$E[(X_t-\mu)^2]=X(0) \text{ and}$$

$$E[(X_t-\mu)(X_{t-\tau}-\mu)]=\rho(\tau) \quad \tau=1,2......$$

Most economic series are not stationary and for stock market prices the evidence suggest the same. This means that the Granger causality test should be performed on differenced data, price changes in my case, since differencing is a suggested way to achieve stationarity. Although my research interest is whether price changes are forecastable, one drawback of the procedure of differencing is that it filters out valuable low frequency information in the data which we need in order to make valid long run inferences about any possible predictive relationships between different stocks.

Recently the concept of cointegration has been suggested as a solution to the above problem. By using cointegration analysis we can capture the valuable long run information contained in the series under investigation. The useful application of cointegration analysis when someone tests the Efficient Market Hypothesis, MacDonald and Taylor (1988, 1989), is based on one very important implication of cointegration theory which says that when two variables are cointergrated then Granger causality runs in at least one direction. As mentioned before causality implies predictability; thus, in an Efficient Market prices, of different stocks cannot be cointegrated, Hall and Henry (1988).

7.3 Cointegration Theory and Tests

The cointegration theory starts from the notion of integration which has has introduced in econometrics by Granger (1981); the basic idea has been in use in the electrical and hydraulic engineering literature for some time. The idea is that the order of integration of a series is given by the number of times a series must be differenced in order to produce a stationary series. Thus, if we difference a series X once to produce a stationary variable ΔX we say that X is integrated of order one denoted by $X \sim I(1)$, and since ΔX is stationary we say that ΔX is integrated of order zero, $\Delta X \sim I(0)$.

The concept of cointegration is the link between integrated processes and the concept of steady state equilibrium. Cointegration was originally introduced by Granger (1981) and extended by Engle and Granger (1987). The cointegration theory lies in the Granger proof that in general if we take a linear combination of two series, each integrated of different order then the resulting series will be integrated at the highest of the two orders of integration. So if $Z_t=bX_t+cY_t$ where $X_t \sim I\ (dx)$ and $Y_t \sim I\ (dy)$ then, in general, $Z_t \sim I\ [\max\ (dx,dy)]$. The above is not always true and it is the exception to this general rule which allow the case for cointegration.

Cointegration may be defined formally as follows, Hall and Henry (1988) : The components of a vector X_t are said to be cointegrated of order d,b (denoted $X_t \sim I(d,b)$) if:

1) All components of X_t are $I \sim (d)$

2) There exists a vector α ($\neq 0$) so that $W_t=\alpha\ X_t \quad I \sim (d-b), b > 0$

with the vector α being called cointegrating vector.

Most work on cointegration has been done for series which are integrated of order one (i.e the first difference of a process produce a stationary series). Thus, if X_t and Y_t series are both integrated of order one $I \sim (1)$ then it is generally true that the linear combination

$$Z_t=Y_t-\alpha X_t \qquad (5)$$

will also be integrated of order one, I~(1). However it is possible that Z_t to be integrated of order zero I~(0). When this occurs, a special constraint operates on the long run components of X_t and Y_t. Since X_t and Y_t are both integrated of order one they will be dominated by long wave components but Z_t being integrated of order zero will not be. Y_t and αX_t must therefore have long run components that virtually cancel out to produce Z_t. In such a case Y_t and X_t are said to be cointegrated with α being the cointegrating parameter.

In another way the basic idea of cointegration is that if in the long run two or more series move closely together, even though the series themselves are trended, the difference between them is constant. We may regard the cointegrated series as defining a long run equilibrium relationship and the difference between them to be stationary. The term "equilibrium" in this case means a relationship which has on average maintained by a set of variables for a long period. Thus Z_t given by (5) measures the extent to which the system (X_t, Y_t) is out of equilibrium and can therefore be termed as the equilibrium error. Hence if Y_t, X_t are both integrated of order one and cointegrated then the equilibrium error term Z_t will be integrated of order zero, and Z_t will rarely drift far from zero, if it has zero mean, and will often cross the zero line. In other words equilibrium will occasionally occur, at least to close approximation, whereas if X_t and Y_t are not cointegrated, so that Z_t will be integrated of order one, the equilibrium error can wander widely and zero crossings would be very rare, suggesting that under such circumstances the concept of equilibrium has no practical implications, Engle and Granger (1987).

The importance of testing whether a pair of integrated time series are cointegrated is obvious. Thus, in the cointegrating regression $Y_t=\alpha X_t+z_t$ where Y_t and X_t are integrated of order one we test if z_t is integrated of order zero. Engle and Granger (1987) suggest many tests of the Hypothesis that X_t and Y_t are cointegrated[4] but the empirical work is dominated by two of them.

The first test is based on the Durbin-Watson statistic D.W. for the cointegrating regression and tests the null Hypothesis that Z_t is integrated of order one. So we test if the D.W. from the cointegrating regression is significantly greater than zero using the critical values provided by Sargan and Bhargava (1983).

The second test examines the residuals from the cointegrating regression, Z_t, directly by performing a unit root test like the Dickey Fuller or the Augmented Dickey Fuller test. The residuals will be integrated of order zero if the Dickey Fuller test give a value, which must be negative, and greater in absolute value from the Dickey Fuller critical values. The Dickey Fuller test was found by Engle and Granger (1987), to have more stable critical values than the D.W test for diferent data sets. In this respect the Dickey Fuller test is preferable when someone tests for cointegration.

The following table (table 2.6) presents the critical values for cointegration between two variables.

TABLE 2.6

Critical Values for test of cointegration

two variables case

	1%	5%	10%
C.R.D.W.	.51	.38	.32
D.F.	-4.07	-3.37	-3.03
A.D.F.	-3.77	-3.17	-2.84

Hall and Henry (1988)

Where C.R.D.W. is the Durbin Watson test for cointegration D.F. the Dickey Fuller test and A.D.F the Augmented Dickey Fuller test. The last two tests will be discussed in detail later when I will test for the order of integration of the variables which I will examine.

The above tests for cointegration sometimes are called static cointegration tests, Jones and Uri (1990). The static cointegration tests, however are not very powerful, in the event that the residual term from the cointegrating regression is stationary but highly serially correlated indicating an autoreggressive pattern, Jenkinson (1986). The Error Correction Models provide another test for cointegration, Engle and Granger (1987). One important result of cointegration theory comes from the Granger representation theorem Granger (1987), which states that if two variables X and Y are cointegrated and I~(1) that is in the model $X_t = \alpha + \beta Y_t + z_t$ where $X \sim I(1)$, $Y \sim I(1)$ $\beta \neq 0$ and z_t

I(0) then there is a pair of Error Correction Models (E.C.M.) of the following form :

$$\Delta X_t = -\rho_1 \hat{z}_{t-1} + f\ (\text{LAGGED } \Delta X_t, \Delta Y_t) + \varepsilon_1$$

$$\Delta Y_t = -\rho_2 \hat{z}_{t-1} + f\ (\text{LAGGED } \Delta Y_t, \Delta X_t) + \varepsilon_2$$

Where $\hat{z}_{t-1}$ the lagged error term from the cointegrating regression which introduces the low frequency information in a short run dynamic system, one of $\rho_1, \rho_2 \neq 0$ and ε_1 ε_2 are finite order moving averages.

Or more formally :

$$\Delta Y_t = -\rho_1 \hat{z}_{t-1} + \sum_{i=1}^{k} \beta_i \Delta Y_{t-i} + \sum_{i=1}^{k} \gamma_i \Delta X_{t-1} + u_{1t} \quad (6)$$

$$\Delta X_t = -\rho_2 \hat{z}_{t-1} + \sum_{i=1}^{k} \delta_i \Delta X_{t-i} + \sum_{i=1}^{k} \zeta_i \Delta Y_{t-1} + u_{2t} \quad (7)$$

where $\hat{z}_{t-1} = X(t-1) - \beta Y(t-1)$, $\rho 1$ or $\rho 2$ are not zero, u_{1t} and u_{2t} are both I (0). Note that in the above Error Correction Models all variables are integrated of the same order, namely order zero.

As a corollary, the Representation Theorem also implies that the converse of the above proposition holds. If X_t and Y_t are both integrated of order one, and there is an error correction model representation with the above properties, then X_t and Y_t are necessarily cointegrated.

The error or equilibrium, term $\hat{z}_{t-1}$ plays a crucial role in the above model. When the variables deviate from the steady state equilibrium for some reason, like a series of abnormally large random disturbances or the systematic effects of a third variable which does not appear in the long run solution, the equilibrium term reduces this deviation and drives the variables back to the long run equilibrium.[5] For this reason the equilibrium term is called error correction mechanism. As Perman puts it *"the error correction term constitutes one case of a systematic disequilibrium adjustment process through which X_t and Y_t are prevented from drifting apart"*, Perman (1991).

According to Granger the above Error Correction Models capture both the short run dynamics and the long run equilibrium between variables X and Y and thus it is possible to draw causal inferences, since as mentioned in a pair of cointegrated variables Granger causality runs in at least one direction. Temporal causal inferences are based on the statistical significance of ρ_1 and ρ_2 and the elements of ΔX_{t-i} and ΔY_{t-i} in (6) and (7). For example, if ρ_1 and the elements of ΔX_{t-i} are different from zero in (6) this gives support for the conclusion that X Granger causes Y. Granger views the possibility that ρ_1 different from zero would indicate long run causality from X to Y while ΔY_{t-i} elements different from zero would indicate short run causality but he also warns that *"it is unclear whether such a view is justified until further analysis is done"* Granger (1988).

It is worth noting at this point that as Granger and Engle (1987) demonstrated when we have a set of N I(1) variables then there may exist r cointegrating vectors between the variables where r=N-1. We therefore need a procedure to estimate all the cointegrating vectors which exist between a set of variables and to test for the distinct cointegrating vectors which exist.

Johansen (1987, 1990), has proposed a method which gives maximum likelihood estimates and a likelihood ratio test statistic (with an exact distribution), for the maximum number of distinct cointegrating vectors in a set of variables. Thus it is possible to identify a whole set of cointegrating relationships using the Johansen method.

8. Empirical Analysis

For the empirical analysis of Market Efficiency which follows, I will use both the Granger causality and cointegration tests. The Granger causality test will indicate any possible short-run predictive interrelationships between the prices of the stocks which I will examine (short-run temporal causality), and cointegration analysis the long-run predictive interrelationships (long-run temporal causality). Statistically, cointegration tests are more informative than the Granger causality tests, although the later can be viewed indicative. Additionally cointegration implies that the possible predictive interrelationship between the examined series has been maintained for a long period of time giving stronger evidence for market inefficiency, since deviations from market efficiency may be observed from time to time but if these inefficiencies do not last for long they may not allow for profitable trading strategies based on them. Finally, the error correction term in the error correction models may take the economic interpretation of the relationship between the examined series which maintains them in a long run equilibrium, where in the Granger causality tests there is not any variable with specific economic interpretation.

8.1 Degree of Integration

In order to perform the above described tests I will try to examine first the order of integration of the examined variables (stock prices). This is required for cointegration tests as well as for the Granger causality tests which are usually performed on stationary variables.

In order to test the order of integration of every variable (stock prices) I used the Augmented Dickey Fuller test which tests if a variable Z_t follows the AR(1) process $Z_t = \rho Z_{t-1} + \varepsilon_t$ where $\rho=1$. The above AR model is a Random Walk model and is integrated of order one. In order to test the above we perform a regression:

$$\Delta Z_t = a_0 + \phi Z_{t-1} + \sum_{i=1}^{n} \gamma_i \Delta Z_{t-i} + \varepsilon_t \quad (8)$$

under the null hypothesis that $\rho=1$ then $\phi=(\rho-1)=0$; if $\rho<1$ $\phi<0$ and we test with a t test if ϕ is significantly less than zero. The t statistic on ϕ is the A.D.F. test statistic with the following critical values[6]:

TABLE 2.7

Critical values for the A.D.F. test

Sample size	Significance level		
	1%	5%	10%
50	3.58	2.93	2.60
100	3.51	2.89	2.58
250	3.46	2.88	2.57
500	3.44	2.87	2.57
∞	3.43	2.86	2.57

Engle and Yoo (1987)

If $\phi<0$ in (8) and absolute value (ϕ)>critical value, then we say that the variable Z_t is integrated of order zero, i.e the examined variable is stationary. If this is not the case we form a new variable $\Delta\Delta Z_t$ and we perform the same type of test on the new variable as follows:

$$\Delta\Delta Z_t = \alpha_0 + \phi\ \Delta Z_{t-1} + \sum_{i=1}^{n}\gamma_i\ \Delta\Delta Z_{t-1} + \varepsilon_t \quad (9)$$

If the new ϕ in (9), is negative and in absolute value greater than the critical value then we may infer that the variable Z_t is integrated of order one, i.e. we have to difference the variable once to produce stationarity. Some researchers proposed that in the above models someone should also include a time trend. Nevertheless, Nelson and Plosser (1982) demonstrate that it would be extremely unlikely that a significant time trend would occour in the presense of a unit root, as this would imply that (for variables in natural logs) the rate of change of the depedent variable is deterministic ever increasing or decreasing; and this kind of behaviour can be ruled out a priory for most economic time series.

Another test often used to examine the degree of integration of a variable is the simple Dickey Fuller test. This test is like the Augmented Dickey Fuller test but without the lagged dependent variables as explanatory variables in the models (8) or (9) but I preferred the A.D.F with lagged dependent variables in order to adjust for high autoregressive or mixed ARMA processes as Engle and Granger (1987) suggest. The A.D.F for the variables which I am examining, corrected for heteroscedasticity when necessary yielded the following results:

TABLE 2.8

Augmented Dickey Fuller test statistics

Stocks	Price Levels		First Differences	
	w/o	w/t	w/o	w/t
1) BANK OF GREECE	-1.23	-1.22	-11.19	-11.24
2) COMMERCIAL BANK	-1.61	-1.80	-11.28	-11.27
3) NATIONAL BANK	-1.19	-1.18	-11.63	-11.71
4) ERGO BANK	-0.11	-0.86	-11.74	-11.76
5) IONIAN BANK	-0.97	-1.15	-11.06	-11.07
6) LIPASMATA	-1.51	-1.17	-11.13	-11.16
7) PIRAIKI	-1.93	-1.11	-11.20	-11.24
8) HALKIDA	-1.30	-1.12	-10.93	-11.01

where w/o stands for the A.D.F test without a time trend, and w/t for the A.D.F with a time trend.

From the above table we can see that, as expected, the prices changes of the examined stocks are stationary and price levels are not, thus the Granger causality tests, will be performed on price changes.

From the stocks in question five are Banks and the rest three industrial firms. Possible predictive interrelationships are more likely to exist between pairs of stocks of the same category, since these possible interrelationships can be explained in economic terms and not only statistically. For the Banks in question the possible interrelationships are obvious. Banks may be related in the field of management, investment strategies, products in the sense that some banks may be leaders in the Banking industry. Additionally, since all Banks belong to the same industry they are influenced more all less from the same factors; the factors which affect the Banking industry. The stock prices of some Banks may respond more quickly to these factors.

The industrial firms in question, which at the first place were selected for their high trading activity, are occupied in different production fields, cement, chemicals and textiles. Nevertheless, the common feature I found for them is that these firms have been categorised for their poor performance as problematic firms and they operated under the supervision of the National Economic Authorities and the Greek Government, suggesting thus some possibility for cointegration.

8.2 Granger Causality Results

The Granger causality test for the models (1) and (2) and for k=20, which as mentioned in the previous chapter represents almost a month, and k=5 which represents almost a week gave the following results:

TABLE 2.9

Granger causality results

Banks

Variable Y	Variable X	F(20)	F(5)	Causality
BANK OF GR	NATIONAL	0.35	0.70	——
NATIONAL	BANK OF GR	0.51	0.90	——
BANK OF GR	IONIAN	0.44	0.87	——
IONIAN	BANK OF GR	0.27	0.08	——
BANK OF GR	COMMERCIAL	0.34	0.53	——
COMMERCIAL	BANK OF GR	0.61	1.05	——
BANK OF GR	ERGOBANK	0.24	0.37	——
ERGOBANK	BANK OF GR	0.71	0.46	——
NATIONAL	IONIAN	0.38	0.62	——
IONIAN	NATIONAL	0.25	0.07	——
NATIONAL	COMMERCIAL	0.21	0.09	——
COMMERCIAL	NATIONAL	0.57	1.12	——
NATIONAL	ERGOBANK	0.24	0.72	——
ERGOBANK	NATIONAL	0.69	0.92	——
IONIAN	COMMERCIAL	0.23	0.31	——
COMMERCIAL	IONIAN	0.63	1.00	——
IONIAN	ERGOBANK	0.59	1.75	——
ERGOBANK	IONIAN	1.14	1.69	——
COMMERCIAL	ERGOBANK	0.68	0.41	——
ERGOBANK	COMMERCIAL	0.63	0.38	——

Industrial Firms

Variable Y	Variable X	F(20)	F(5)	Causality
HALKIDA	PIRAIKI	0.36	0.91	——
PIRAIKI	HALKIDA	0.19	0.13	——
HALKIDA	LIPASMATA	0.39	0.67	——
LIPASMATA	HALKIDA	0.65	1.58	——
PIRAIKI	LIPASMATA	0.12	0.05	——
LIPASMATA	PIRAIKI	0.41	1.35	——

The critical values for the F test in the case of the twenty variables is 1.71 at 5% significance level and 1.57 at 10% significance level and for the case of five variables the critical values are 2.57 and 2.21 respectively. The symbol —— in the above results denotes no Granger causality.

From the above results the Granger test clearly suggests that there is not any linear temporal causality between the examined stocks. Nevertheless, as the lag length was reduced from twenty to five lags the F statistic increased indicating the importance of the most recent values of the explanatory variables, but still was lower than the critical value at 5%.

8.3 Cointegration Results

In order to investigate if there exists long-run or equilibrium predictive relationship between the examined stocks I will test for the possibility of cointegration. If the results indicate that a pair of stock prices are cointegrated I will investigate through the Error Correction Models if the Granger causality implies market inefficiency.

As has been mentioned earlier in a set of variables X_t Y_t which are integrated of the same order and integrated of order one we cantest for cointegration by regressing one on the other and testing if one is significant in explaining the other and the residuals from the above regression are integrated of order zero. Thus, I will regress the price level of stock Y on the price level of stock X, which are both integrated of order one, and according to the cointegration criteria I will test if the error term from the cointegrating regression is integrated of order zero.

I performed the C.R.D.W. and A.D.F. tests for cointegration on the pairs I am examining, and according to the results only three pairs of stocks appeared to be possibly cointegrated and these stocks are the stocks of the industrial firms LIPASMATA, PIRAIKI, HALKIDA.

Analytically, for these pairs, I obtained the following results[7]:

TABLE 2.10

Cointegration results

Pairs		A.D.F test statistic	C.R.D.W
PIRAIKI	LIPASMATA	-3.37	0.05
PIRAIKI	HALKIDA	-3.60	0.03
LIPASMATA	HALKIDA	-4.01	0.06

From the above results we can see that although the C.R.D.W. statistic is very low, the A.D.F. test on the residuals indicate cointegration. As noted before Engle and Granger (1987), prefer the A.D.F. test when testing for cointegration, noting that the C.R.D.W. *"might be used for a quick approximate result"*. In addition, Sargan and Bhargava (1983), find that the power of the C.R.D.W. test for Random Walk, which indicates non stationarity, against the alternative hypothesis that $u_t = \rho u_{t-1} + \varepsilon_t$, becomes very low as ρ approaches unity. For my results the C.R.D.W. indicates a very high ρ but not equal to unity as calculated by the formula C.R.D.W.=2(1-ρ). As mentioned before in the case of highly autocorrelated error term Jenkinson (1987) suggests the Error Correction Models is a better test for cointegration. In the case of cointegration one of the terms z_{t-1} in (6) or (7), which when cointegration holds are negative, Engle and Yoo (1987), should be significantly different from zero.

I tried the Error Correction models (6) and (7) for the possible cointegrated pairs following the Granger and Engle (1987) suggestion to overparametrise the models and then drop all the insignificant lagged variables from the equations.[8] In the initial overparametrised Error Correction Models I used ten lags of both the dependent and independent variables. After simplification I obtained the following results:

TABLE 2.11

Error Correction Models Results

Pair: Halkida (ΔY), Lipasmata (ΔX)

Depedent Variable ΔY			Depedent Variable ΔX		
Variables	Est.	"t"	Variables	Est.	"t"
ΔY_{t-1}	0.05	2.11	ΔX_{t-1}	0.03	1.05
ΔY_{t-4}	-0.03	1.27	ΔX_{t-3}	-0.11	2.71
ΔY_{t-5}	-0.07	1.76	ΔY_{t-3}	1.47	2.33
ΔX_{t-5}	0.003	1.26	ΔY_{t-10}	0.47	1.15
ΔX_{t-6}	-0.003	1.83	E.C.T	-0.02	2.12
E.C.T	-0.009	1.04			
R^2=0.01	$LM_{(23)}$=4.64		R^2=0.01	$LM_{(23)}$=3.37	
$ARCH_{(1)}$=0.07			$ARCH_{(1)}$=0.007	P.S.T=0.11	

Pair: Piraiki (ΔY), Halkida (ΔX)

Depedent Variable ΔY			Depedent Variable ΔX		
Variables	Est.	"t"	Variables	Est.	"t"
ΔY_{t-1}	0.02	0.93	ΔX_{t-1}	0.06	2.25
ΔY_{t-9}	-0.05	1.08	ΔX_{t-2}	-0.05	1.11
ΔX_{t-9}	0.30	1.00	ΔX_{t-4}	-0.09	1.94
ΔX_{t-11}	0.02	1.37	ΔY_{t-2}	0.007	1.01
E.C.T	-0.01	1.80	ΔY_{t-4}	-0.01	1.38
			E.C.T	-0.005	0.75
R^2=0.005	LM(23)=5.68		R^2=0.008	LM(23)=7.09	
ARCH(1)=0.32	P.S.T=0.09		ARCH(1)=0.12		

Pair: Lipasmata (ΔY), Piraiki (ΔX)

Depedent Variable ΔY			Depedent Variable ΔX		
Variables	Est.	"t"	Variables	Est.	"t"
ΔY_{t-1}	0.02	0.82	ΔX_{t-1}	0.04	0.83
ΔY_{t-3}	-0.13	2.76	ΔY_{t-1}	-0.09	0.43
ΔX_{t-3}	0.24	2.20	ΔY_{t-4}	-0.01	1.16
E.C.T	-0.01	1.17	ΔY_{t-9}	-0.009	0.77
			E.C.T	-0.01	1.50
R^2=0.01	LM(23)=4.64		R^2=0.01	LM(23)=3.37	
ARCH(1)=0.07			ARCH(1)=0.007	P.S.T=0.11	

Where in parenthesis are the "t" ratios in absolute values, L.M is the Langrange multiplier test for autocorrelation, ARCH a test for Conditional Heteroscedasticity and PST a prediction stability test for the models for a period of five months out of the estimation sample.

From the above results we can see that the stocks of PIRAIKI HALKIDA and LIPASMATA are indeed cointegrated and the Granger causality runs between these stocks as follows: HALKIDA and LIPASMATA give the strongest evidence for cointegration; they are cointegrated at 5% significance level, a one tailed test appears appropriate since the Error Correction Term must be of negative sign for a cointegration relationship to hold. The long run causality runs from HALKIDA, that is in the long run HALKIDA causes LIPASMATA and if we dare a short run causality conclusion we can say that again HALKIDA causes LIPASMATA.

The pairs PIRAIKI HALKIDA are cointegrated at 5 % significance level but less strongly than the previous pair the causality runs from HALKIDA i.e., HALKIDA causes in the long run PIRAIKI. Finally LIPASMATA and PIRAIKI are weakly cointegrated at 10 % level and the causality runs from lipasmata i.e LIPASMATA cause in the long run PIRAIKI.

The L.M and ARCH statistics indicate that the error term in the above models does not exhibit any autocorrelation or heteroscedasticity. Finally, the prediction stability test indicates that the prediction validity of the models in an out of the estimation period of five months is very good.

8.4 Trading Rule

Since the Error Correction Models give statistical evidence that the price changes of a stock can be predicted by the lagged price changes of another stock and the lagged equilibrium relationship between the two stocks, I will try to test if the above findings can be proved useful for the formation of a profitable trading rule. The Efficient Market Hypothesis will be violated only if the statistical evidence against it can be proved profitable.

The trading rule for this new evidence against the Efficient Market Hypothesis will be of the same form as the trading rule of the previous chapter. If the forecast price change from the Error correction models is positive (expected price increase) and covers the transaction costs per share, then someone buys the stock and holds it until the predicted price change from the Error correction model is negative and larger in absolute value than the transaction costs per share, then someone sells the stock and holds cash. Since for the above Error Correction Models the predictive stability tests indicated that the models perform well in an out of the estimation period of five months I tryied the trading rule for all the period under examination.

The above trading strategy for the cointegrated pairs of stocks, when was simulated with a computer program, and when brokerage costs were taken into account, outperformed the Buy and Hold strategy in all cases, indicating that the statistical results are evidence against the Efficient Market Hypothesis indeed.

TABLE 2.12

Trading Rule Results based on

the Error Correction Models

(in Wealth units)

	Piraiki(1)		Piraiki(2)		Lipasmata	
Day	B & H	T/R	B & H	T/R	B & H	T/R
1	100	100	100	100	100	100
100	74	95	78	102	80	114
200	76	92	76	136	96	175
300	62	89	62	116	79	146
400	45	77	47	108	55	163
500	34	68	34	121	33	141
600	14	68	14	115	25	108
700	10	70	9	77	24	111
800	12	87	12	93	26	127
900	11	85	12	99	24	115
1000	15	118	16	138	29	147
1100	14	107	14	140	27	144
1200	10	127	18	132	35	131

Column Piraiki(1) refers to the error correction model where Piraiki is the dependent variable and Lipasmata the explanatory, column Piraiki(2) to the model where Piraiki is the dependent variable and Halkida the explanatory and the column Lipasmata refers to the model where Lipasmata is the dependent variable and Halkida the explanatory, finally, wealth is as defined before.

8.5 Summary

In this chapter I investigated statistically the Weak form of Market Efficiency i.e., if there is information in the history of prices which can help to predict profitably price changes. In the first place the information set I used to test the Efficient Market Hypothesis included only the price history of the stock in question; for example, for stock j the information set was $I_{t-1}=[\Delta P_{j}, _{t-1}]$. The results the statistical analysis indicated that price changes are not independent in high and low frequencies.

Following the Box-Jenkins technique I discovered that there are models which can describe price changes better than the random walk model. These models emerged from the high positive first lag autocorrelation of price changes which was a common feature of all the examined stocks. The forecasts based on these models proved to be profitable since a trading strategy based on these models outperformed the Buy and Hold strategy. Spectral analysis indicated that price changes are also correlated at low frequencies since none of the price changes periodograms was similar to the periodogram of an uncorrelated series. The shape of the periodograms instead confirmed the AR nature of the price changes. Nevertheless, no profitable trading rule could be formed on the basis of the low frequency correlation of price changes. The result of the above analysis was that the static expectations model $P_t^*=P_{t-1}$ is not adequate to describe the data and that a model of the form $\Delta P_t^*=\alpha\Delta P_{t-1}$ with $\alpha>0$, seems consistent with the data.

In the second part of this chapter I tried to investigate if there are any predictive interrelated pairs of stocks i.e., for a stock j the information set I used to test the Efficient Market Hypothesis was $I_{t-1}=[\Delta P_{i,t-n}]$, where i a stock other than j. Granger causality tests indicated the the above information set is useless to predict the price changes of the stocks in question. Nevertheless, cointegration analysis indicated that some of the Granger causality tests were mispecified by excluding from their specification the price levels which are captured by the error correction term in the error correction models. Thus if in the above information set, $I_{t-1}=[\Delta P_{i,t-n}]$, we also include the error correction term of the long run relationship between a pair of cointegrated stocks, $I_{t-1}=[\Delta P_{i,t-i},\hat{z}_{t-1}]$, where z_{t-1} the error correction term, then this information set can be prove useful in forecasting price changes profitably, since a trading strategy based on the forecasted price changes from cointegration analysis was used outperformed the Buy and Hold strategy.

Notes

1.

According to the minimum variance criterion, Pokorny (1980), a variable becomes stationary for the difference transformation with the smallest variance. For instance if we consider the transformations X, ΔX and $\Delta\Delta X$ for a variable X and $var(X)>var(\Delta X)$ and $var(\Delta\Delta X)>var(\Delta X)$ then according to the minimum variance criterion variable X should be differenced once to produce stationarity.

2.

Trading in the Athens Stock Exchange takes place between 8.30 a.m to 12.30 p.m every working day and on the basis of an auction system in which all stocks are traded in the same time.

Cash orders exist in the Athens Stock Exchange. Specifically a cash transaction means that the settlement of a transaction executed during a day's trading period should be made on the next morning. Under normal trading conditions the back office operations of the A.S.E. are quite efficient.

3.

There are no capital gain taxes in Greece and also no company tax as such. The income of fixed interest securities is comletly tax free. The income from dividends of companies quoted in the A.S.E. is exempted from income tax up to fifty thaousand Drachmae for each company and up tp two hundred thaousand Drachmae for all of them per year. In other cases the tax is 42%-45% of the dividend income.

The brokers commissios in the A.S.E. is 0.5% for an amount of money more than three million Drachmae, 0.75% for an amount of money between two millions and three millions and 1% for an amount of money less than one million Drachmae.

4.

Engle and Granger (1987), report a number of alternative tests for cointegration e.g. RVAR, ARVAR wich in fact test for the significance of the Error Correction Term in Error Correction Model formulations.

5.

More than one lag in the Error Correction Models are unecessary. The effects of additional lagged error correction terms are already captured in the distributed lags of the first differences of X_t and Y_t Engle and Granger (1987).

6.

Guilkee and Schmidt (1989), present extended tabulations for thew Dickey Fuller test.

7.

For the pairs of Banks I obtained the following results:

Variables	CRDW	ADF statistic
Bank of Greece, National	0.02	-1.45
Bank of Greece, Commercial	0.01	-0.84

Bank of Greece, Ionian	0.01	-1.01
Bank of Greece, Ergobank	0.01	-1.76
Ionian, National	0.006	-0.58
Ionian, Commercial	0.02	-1.89
Ionian, Ergobank	0.03	-3.01
Commecial, Ergobank	0.01	-2.08
Commercial, National	0.007	-1.56
National, Ergobank	0.008	-1.56

8.

There are also alternative techniques for determining the lag structure of the Error Correction Models. First, is to use some model selection criteria like Akaike's criteria. However such aprocedure is likely to result in reduced power of the test, Engle and Granger (1987), Jones and Uri (1990). Thus the most common method is Hendry's general to specific in which we start with an overparametrised model and eliminate the lags with insignificant parameter estimates.

TESTING THE SEMISTRONG FORM OF EFFICIENCY IN THE ATHENS STOCK EXCANGE

Chapter Three

1. Testing the Semistrong Form of Efficiency in the Athens Stock Exchange

Overview

In the previous chapters I examined the Fama's Weak Form of Market Efficiency on the basis of daily data. In this chapter I move from daily data into monthly data and after I will have examined for possible predictive relationships between the stock market indices of the A.S.E. I will investigate statistically the Semistrong form of Market Efficiency as defined by Fama in 1970, i.e., I will test how, if at all, index prices react to past available information other than the "histories of past prices".

Apart from the flow of information individual to each firm listed in a stock market, there are some major political and economic occurrences which simultaneously affect the prices of many stocks. Consequently prices of individual stocks or indices can be expected to move together to a certain extent due to the so called Market Factor. A typical regression model of the form:

$$Y_{it} = a \bar{X}_t + \varepsilon_t \qquad (1)$$

where Y_{it} is the return on stock i at time t, $\bar{X}_t$ a vector of variables which comprise the Market Factor at time t like Inflation rates, Money Supply measures, Interest rates, and ε_t is white noise, should yield an R^2 which explains to some extent the reaction of stocks to the

Market Factor. In the above model the addition of lagged independent variables should not improve the fit of the model in an Efficient Market, since in such a market only variables contemporaneous to the return may have explanatory power. The opposite case would imply the existence of a predictive model and possible violation of the Efficient Market Hypothesis if a trading rule based on the predictive model prove to be better than the Buy and Hold strategy.

It is arguable at this point that this test is a test for the Weak Form of market efficiency i.e., if returns are forecastable. Fama in his 1991 paper "Efficient Capital Markets II", *"at the risk of damning a good thing"* changes his 1970 definitions for the versions of market efficiency to the following ones: Weak Form:"*..This category covers the more general area of test for return forecastability, which includes the burgeoning work on forecasting returns with variables like dividend yields, and interest rates*". For his 1970 Semistrong Form, Fama in 1991 says: *"Instead of Semistrong tests of the adjustment of prices to public announcements, I use now the common title event studies*". Thus, according to Fama in 1991 the statistical tests which will follow are tests for the Weak Form of Market Efficiency since this statistical analysis can not be characterised as an event study (see ch 1). Nevertheless, since Fama's definition in 1970 dominates in the Finance literature I consider the tests which will follow the part for predictive interrelationships between stock market indices, as tests for the Semistrong form of market efficiency.

The information set which I will use to test the Semistrong Form of Market Efficiency will include Macroeconomic variables which theoretically should affect stock prices and other variables which investors may take into account for their investment decisions. The literature devoted to estimating the determinants of stock prices is quite diverse and there are no commonly accepted econometric models, though, as already mentioned, money supply measures, interest rates, rates of inflation, exchange rates, even ladies hemlines (Malkiel 1970), have been widely used to predict movements in stock prices.

2 The Data

For the statistical analysis I used the returns (defined as price relatives i.e. $(P_t/P_{t-1})-1$ exclusive of dividends payments) and price levels from ten stock market indices which represent nine industries in the Greek economy. Analytically, I used the following indices:
Banks index, Insurance firms index, Textile firms index, Steel firms index, Building Construction firms index, Food firms index, Chemical firms index and Miscellaneous firms. I also used two general indices, which refer to the Banking and the Industrial sector separately. The examined period is eight years, on a monthly basis, from January 1981 through December 1988.

Monthly data unfortunetly may not be as informative as high frequency data e.g. daily data, but gor the Greek economy the most of the Maroeconomic variables are published on a monthly basis, thus the examination of the semistrong form of market efficiency must be performed on monthly data sets.

One important element of the variables which I will use, which is of great importance for the statistical tests for the Efficient Market Hypothesis which will follow, is that these variables must not be contemporaneous with stock returns. In order to make clear this point lets us assume that in the model where the return at time t is the dependent variable one explanatory variable let us say X proves to be significant at lag t-i. The above statistical evidence it is not an evidence against the Efficient Market Hypothesis unless the variable X is known to investors (announced) prior to time t. If on the contrary the variable which refers to t-i is announced at time t this cannot be treated as an evidence against Market efficiency since this variable is considered to be contemporaneous with the return at time t.

3. Tests for Predictive Interrelationships between Stock Indices of the Athens Stock Exchange

In the first place, before I examine if there is any predictive value of several economic variables on stock returns, I will test the Efficient Market Hypothesis by investigating if there are any predictive interrelationships between the possible pair combinations of the examined indices. For instance, a statistical result that the return of index X helps to predict the return of index Y would imply possible violation of the Efficient Market Hypothesis. Thus, I will test the Efficient Market Hypothesis with respect to the information set $I_{t-1}=[R_{t-i}]$, where R_{t-i} is a vector of returns of an index other than the returns of the examined index, and i=1,2....,n.

The economic reasoning for searching for causality relationships is that since all stocks (indices), are influenced by the Market Factor it may be true that some indices react slowly to this factor and thus Granger caused by the more responsive indices. In addition sinse the examined indices represent different industries in the Greek economy they may be interrelated financially or in the field of production i.e. the output of one sector may be input for another sector. Thus, they may be influenced by common factors and again some indices may be more responsive to these factors than others e.g. some news about the chemical industry (fertilisers) may be reflected with some dalay on the food industry (agriculture production).

In order to perform the above tests I will again usethe Granger causality and cointegration tests as described in the previous chapter. I have to note here that sinse there are 45, (1+2+...+9), pair combinations of stock indices it is expected that we find some causalities due to chance. In order to minimise this possibility we will consider as valid results those where the Granger causality test and the cointegration analysis are in agreement, that is the cases where we may have evidence of inefficiency in both high and low frequencies. In addition in order to avoid the problem of model misspecification in the Granger causality tests by excluding the price levels from the model specification we will put more weight to the cointegration results i.e. even when the Granger causality tests indicate no violation of the efficient market hypothesis we will test for cointegration and we will accept the efficient market hypothesis only if cointegration analysis gives supporting evidence for its validity. Thus in the case where the Granger causality tests indicate market inefficiency we will accept this result only if it is consistent with cointegration analysis.

3.1 Degree of integration

Before the econometric analysis for predictive relationships I will test for the degree of integration of the variables which I will use, since some of the econometric tests which I will employ, as already known (ch 2), require stationary data. In order to test if the variables (index returns) are stationary or not I used the Augmented Dickey-Fuller test (ch 2). The A.D.F. test for the examined variables yielded the following results[1]:

Index	A.D.F. test statistic
Banks	-5.63
Insurance	-7.79
Textiles	-4.76
Food Ind	-4.79
Miscellaneous	-5.73
Steel Ind	-6.54
Building Ind	-5.68
Chemicals	-5.81

The above results, agree with the existing evidence that returns are stationary, since all statistics are negative and statistically significant. These results indicate that the series I will use are in a state of statistical equilibrium and no econometric problems arise in the tests which I will perform.

3.2 Granger causality tests

In order to see if there are any indices which cause (precede) others I used the following formulations of the Granger causality test:

$$R_{x,t} = \alpha + \sum_{j=1}^{n} \beta_j R_{x,j-t} + \sum_{j=1}^{n} \gamma_j R_{y,j-t} + \varepsilon_t \qquad n=12 \qquad (1)$$

$$R_{y,t} = \alpha + \sum_{j=1}^{n} \delta_j R_{y,j-t} + \sum_{j=1}^{n} \zeta_j R_{x,j-t} + v_t \qquad n=12 \qquad (2)$$

Where $R_{x,t}$ is the return of index X at time t, $R_{y,t}$ the return of index Y at time t, and $R_{x,j-t}$, $R_{y,j-t}$ the returns of indices X and Y from t-1 to t-12. As noted in the previous chapter (ch 2) a related issue regarding tests of causality is the determination of the appropriate finite lag lengths for the two variables. The usual practice as already mentioned (ch 2) is to use a lag length that ensures white noise residuals, which is a requirement for Granger causality tests. To ensure theoretically white noise residuals I used a twelve lag length as the econometric practice for monthly observations suggest. In the above regressions as already known (ch 1) I will test if the coefficients γ_j and ζ_j are equal to zero $\gamma_j=0$, $\zeta_j=0$.

If these coefficients are different from zero in one of the models and ε_t, v_t fulfill the requirements of the Granger causality tests (ch.2), then the Efficient Market Theory will be possibly violated. In the cases where both sets of coefficients are equal to zero then it is not possible to make any causality inferences, since the two series will not be temporally related to each other, and the Efficient Market Theory will hold. Finally, in the case where both coefficients are different from zero it will not be clear which variable precedes the other. This bidirectional causality would imply Market Efficiency since there is not a clear prediction relationship, (Morkerjee).

From the Granger causality tests I obtained the following results:

TABLE 3.1

Granger Causality results

VARIABLES Y	X	F Statistics		Causality
BANKS	INSURANCE	$F_1=4.19^{**}$	$F_2=4.30^{**}$	<———>
BANKS	TEXTILES	$F_1=2.11^{*}$	$F_2=1.98^{*}$	<———>
BANKS	MISCELLAN.	$F_1=1.59$	$F_2=1.81$	———
BANKS	FOOD IND	$F_1=1.75$	$F_2=4.62^{**}$	———>
BANKS	CHEMICALS	$F_1=1.89^{*}$	$F_2=2.25^{*}$	<———>
BANKS	BUILDING	$F_1=2.27^{*}$	$F_2=1.75$	<———
BANKS	STEEL	$F_1=0.54$	$F_2=1.80$	———
INSURANCE	TEXTILES	$F_1=3.21^{**}$	$F_2=5.53^{**}$	<———>
INSURANCE	FOOD IND	$F_1=5.23^{**}$	$F_2=4.43^{**}$	<———>
INSURANCE	CHEMICALS	$F_1=3.73^{**}$	$F_2=1.21$	<———
INSURANCE	MISCELLAN	$F_1=4.14^{**}$	$F_2=3.52^{**}$	<———>
INSURANCE	BUILDING	$F_1=5.44^{**}$	$F_2=1.48$	<———
INSURANCE	STEEL IND.	$F_1=2.77^{**}$	$F_2=0.88$	<———
TEXTILES	MISCELLAN	$F_1=0.52$	$F_2=1.06$	———

TEXTILES	FOOD IND	$F_1=5.15^{**}$	$F_2=2.84^{**}$	<———>
TEXTILES	CHEMICALS	$F_1=1.38$	$F_2=1.42$	———
TEXTILES	BUILDING	$F_1=3.91^{**}$	$F_2=1.18$	<———
TEXTILES	STEEL IND	$F_1=1.81$	$F_2=1.55$	———
MISCELLAN	FOOD IND	$F_1=3.56^{**}$	$F_2=2.50^{**}$	<———>
MISCELLAN	CHEMICALS	$F_1=0.67$	$F_2=0.45$	———
MISCELLAN	BUILDING	$F_1=3.91^{**}$	$F_2=0.64$	<———
MISCELLAN	STEEL IND	$F_1=2.01^{*}$	$F_2=1.14$	<———
FOOD IND	CHEMICALS	$F_1=2.80^{**}$	$F_2=3.30^{**}$	<———>
FOOD IND	BUILDING	$F_1=7.09^{*}$	$F_2=1.66$	<———
FOOD IND	STEEL IND	$F_1=3.40^{**}$	$F_2=2.22^{*}$	<———>
CHEMICALS	BUILDING	$F_1=5.44^{**}$	$F_2=0.97$	<———
CHEMICALS	STEEL IND	$F_1=2.12^{*}$	$F_2=1.66$	<———
BUILDING	STEEL IND	$F_1=0.87$	$F_2=1.71$	———

Where ——> implies the direction of the Granger causality, e.g ———> means Y Granger cause X, ——— implies no Granger causality and <———> bidirectional Granger causality. F_1 refers to the regression where Y is the dependent variable and F_2 to the regression where X is the dependent variable. Single star denotes statistical significance at 5% significance level and double star significance at 1% significance level. Again when necessary for the estimation of the Granger causality tets we used a heteroscerstic consistent covariance matrix according to White (1980).

The above results suggest that there are some one side Granger causalities which may imply market inefficiency. An examination of the above Granger sausality results indicates that the return of the Insurance index is the one which is Granger caused by the highest number other indices returns and that the return of the Building

Construction index is the one which Granger cause the highest number of other index returns.

3.3 Cointegration Analysis

As already known among the weaknesses of the above test is that the stationarity of the variables results ina loss of useful long run information contained in the data (ch 2). In order to utilise the long run information contained in the data in terms of prediction and toobtain more robust statistical results, I used again the concept of cointegration both static and dynamic (ch 1.). The cointegrating regressions have the form:

$$I_{xt}=a+ bI_{yt}+ z_t \qquad (3)$$

where I_{xt} and I_{yt} are the price levels of indices X and Y at time t which are integrated of order one.

The cointegration tests on the residuals of the cointegrating regressions yielded the following results which are consistent with cointegration[2].

TABLE 3.2

Cointegration results

Variable Y	Variable X	CRDW stat.	A.D.F test stat.
INSURANCE	BANKS	0.64**	-4.23*
TEXTILES	BANKS	0.79**	-5.03**
INSURANCE	MISCELLANEOUS	0.87**	-5.74**

Where CRDW is the Sargan Barghava cointegration Durbin Watson statistic and A.D.F. the Augmented Dickey Fuller statistic. In the above results single star denotes statistical significance at 5% and double star statistical significance at 1%. The above results indicate cointegration and thus Granger causality. In order to exploit the direction of the Granger causality and see if it indicates Market inefficiency I used the Error Correction models.

From the Error Correction Models, after simplification, I obtained the following results:

TABLE 3.3

Error Correction Models Results

Pair: Banks (Y), Textiles (X)

Depedend Variable: Y			Depedend Variable: X		
Variables	Est.	"t"	Variables	Est .	"t"
ΔY_{t-1}	-0.28	1.75	ΔX_{t-7}	0.54	2.38
ΔY_{t-7}	0.34	2.12	ΔY_{t-7}	1.90	3.05
ΔY_{t-10}	0.13	1.25	E.C.T	-0.56	3.63
ΔX_{t-3}	0.06	1.48			
ΔX_{t-9}	0.20	4.76			
E.C.T	-0.31	2.45			
R^2=0.40 LM(12)=18.72			R^2=0.18 LM(12)=19.94)		
ARCH(1)=8.43			ARCH(1)=3.47		

Causality: Banks ——> Textiles

Pair: Insurance (Y), Banks (X)

Depedend Variable: Y			Depedend Variable: X		
Variables	Est.	"t"	Variables	Est.	"t"
ΔY_{t-2}	0.17	4.34	ΔX_{t-1}	0.49	3.49
ΔY_{t-7}	-0.32	1.79	ΔX_{t-2}	0.63	4.43
ΔX_{t-2}	-1.13	3.93	ΔX_{t-7}	0.44	2.50
ΔX_{t-7}	0.72	2.02	ΔY_{t-1}	-0.19	2.32
ΔX_{t-9}	-0.43	2.03	ΔY_{t-2}	-0.46	5.52
E.C.T	-0.36	2.98	ΔY_{t-4}	-0.08	1.96
			ΔY_{t-7}	0.21	2.46
			ΔY_{t-9}	-0.30	6.22
			E.C.T	-0.10	1.44
R^2=0.39 LM(12)=18.01			R^2=0.59 LM(12)=15.10		
ARCH(1)=4.90 PST=1.05			ARCH(1)=4.32		

Causality: Banks ——> Insurance

Pair: Insurance (Y), Miscellaneous (X)

Depedend Variable: Y			Depedend Variable: X		
Variables	Est.	"t"	Variables	Est.	"t"
ΔY_{t-2}	1.30	7.03	ΔX_{t-1}	0.17	2.03
ΔY_{t-7}	-0.16	2.04	ΔX_{t-2}	0.77	3.86
ΔX_{t-2}	-2.02	6.73	ΔY_{t-3}	-0.63	4.97
ΔX_{t-6}	0.29	2.29	ΔY_{t-4}	-0.13	2.49
E.C.T	-0.28	2.15	ΔY_{t-7}	-0.11	2.17
			E.C.T	-0.42	1.51
R^2=0.51 LM(12)=16.32			R^2=0.41 LM(12)=19.13		
ARCH(1)=1.21 PST=3.02			ARCH(1)=2.85		

Causality: Miscellaneous ——> Insurance

Where "t" are the t ratios in absolute values, L.M the Lagrange Multiplier test for autocorrelation, ARCH a test for Heteroscedasticity and PST a prediction stability testfor an out of the estimation period. The symbol ——> indicates the direction of the Granger causality. Finally in all the above models all variables are integrated of order zero as is required.

The above Error Correction Models results indicate cointegration since the Error Correction Term is negative and significant in at least one error correction formulation for each pair. The results give statistical evidence that the Insurance index is Granger caused from other indices of the Athens Stock Exchange. Additionally, from the results it seems that the Banking index Granger cause the indices of the Insurance firms and the Textile firms. The Building Construction index which according to the simple Granger causality tests seemed to be a leading index in the Athens Stock Exchange did not indicate such a leading behaviour from the cointegration analysis. Nevertheless, the majority of the pairs under examination were not found to be cointegrated. Thus we have to conclude that the majority of the stock market indices react very quickly, and thus contemporaneously, to the Market Factor or that their possible relationships in the finance or production fields are efficiently discounted by the market participants, in other words for the examined period and for the specific information sets the majority of the empirical tests indicated that the Athens Stock Exchange is an efficient market.

For the case of the cointegrated pairs, the prediction stability test in the above error correction models indicated that onlythe model for the pair Banks-Insurance maintain its forecasting validity in an out of the estimation sample period. A trading rule similar to the one in the previous chapter, based on the predicted values of the estimated E.C. model, outperformed the Buy and Hold strategy in the period under examination , indicating that the E.M.H for the pair Banks-Insurance is indeed violated.

TABLE 3.4

Trading rule results for the Insurance index.

Explanatory variable Banks index.

(in Wealth units)

Month/Year	B & H	T/R
1/81	100	100
6/81	99	99
12/81	116	116
6/82	90	89
12/82	114	136
6/83	102	142
12/83	106	141
6/84	111	145
12/84	126	150
6/85	145	161
12/85	165	171
6/86	142	170
12/86	189	225
6/87	241	287
12/87	396	900
6/88	359	824
12/88	387	824

4. Interpretation of the Cointegration Results

The cointegration tests in chapter one and in this chapter indicated that in the Athens Stock Exchange there are some leading stocks and stock market indices since cointegration implies precedence. In chapter one I found that three stocks in unrelated fields of business (textiles, cements, chemicals) were cointegrated. The cement firm led the other two and the chemical firm the textile firm. In this chapter I discovered mainly a lagging behaviour of the Insurance sector of the Greek stock market.

When two stock price series or stock indices series are found to be cointegrated, this implies that the series in question exhibit a long run equilibrium relationship and a possible explanation for this equilibrium relationship is that the firms or industries in question are interrelated. It would be interesting I think for someone to investigate if such relationships exist and try to interpret them e.g. the firms or industries under investigation may be interrelated in the production or consumption fields or they may be financially interrelated. In an Efficient Market such relationships are known to the market participants and the interrelated stocks/indices should react simultaneously to the news which concern them.

In the previous statistical analysis the cointegration results indicated that the interrelated stocks/indices are not affected simultaneously by the news. The above evidence can be interpreted as a direct market inefficiency in the following sense. Stocks/indices X and Y are interrelated but the market may not know this interrelationship. If the market was aware of such a relationship the interrelated stocks/indices should react simultaneously and there would not be any evidence of causality. From the statistical results it seems that when news comes into the market which affect the leading stock/index say X and then this news may be reflected with a delay on the lagging stock/index say Y because of its relationship with stock/index X.

The cointegration results indicate that in the Athens Stock Exchange there are some interrelationships between stocks/indices which have not been discovered by the market. In this case the Error Correction Term which represents the mechanism which holds the examined series in equilibrium can be explained theoretically as the relationship between the stocks/indices X and Y which has not been discovered by the market participants.

This point needs a bit more elaboration. When stocks/indices X and Y are characterised by some relationship then these stocks/indices are at some equilibrium with respect to that relationship. When news comes into the market itaffects for some reason first the leading stock/index and this is a disturbance for the equilibrium state between the stocks/indices. Then this news is reflected on the lagging stock /index because of its relationship with the leading stock/index bringing the two back into equilibrium. I think that it would be interesting here to investigate the possible interrelationships which may exist between the cointegrated stock indices and firms. Such an analysis is difficult and the proposed scenarios are hypothetical but the most likely.

The cointegration results in ch 1. indicated that three stocks namely Halkida (Cements), Lipasmata (Chemicals) and Piraiki (Textiles) exhibit a positive long run relationship in the examined period. The Granger causality runs from Halkida to Lipasmata and Piraiki and from Lipasmata to Piraiki. The above results are at a first glance surprising. Someone could reasonably ask how these firms which are occupied in different production fields can be interrelated.

The most reasonable answer is based on the fact that the above firms had a very poor performance in the Greek economy, and for this reason have been taken under the supervision of the Greek government, i.e., the cointegrating firms are interrelated in the management and finance fields. Thus, common news about these firms was primarily news about the government policy for these firms. The policy taken by the government for one of these firms, usually high subsidies, was followed by the same policy for the other through a spillover procedure. Nevertheless, the reasons which led these firms to financial distress were different among them and the general subsidy policy was ineffective (Table 1). I have to mention here, that recently the unsuccessful subsidy policy has changed to the privitization solution. It seems that the Greek investors failed to understand this fact i.e. the spillovers of the inefficient government policy, because if they had, the causality would not have existed i.e the inefficient goverment polocy would have been efficiently discounted and these stocks would react to news other than news concerning the inefficient goverment policy.

TABLE 3.5

Cumulative Profits/Losses (in millions)

Year	Piraiki	Lipasmata	Halkida
1982	-2.033	-810	-494
1983	-5.055	-808	-2.083
1984	-11.054	-470	-5.633
1985	-19.519	0,76	10.060
1986	-23.649	0,84	17.631

(Source:The Official Balance Sheets)

For the case of the cointegrated indices it is reasonable to argue that the lagging indices may respond with some delay to the news which affects all stocks but also it can be argued that the causality emerged because of some interrelationship between the cointegrated indices.

For the case of the Insurance firms it has been found that its index is Granger caused by the indices of Banks, and Miscellaneous firms. One possible explanation relies on the fact that the Insurance firms investment strategy is to hold securities of other firms listed in the A.S.E. As the following table (Table 2) indicates, the investment stracture financial ratio:

Participation in securities / Total current assets

is very high for the Insurance firms in comparison with the Banking sector. It is also true that the Investment income is a major source of income for the Insurance firms. Thus, it may be true that news which affect the portfolio of the insurance firms affects their profits and consequently their price.

TABLE 3.6

Insurance Firms	P.S / T.C.A	Banks	P.S / T.C.A
ASTIR	0.37	ATTIKIS	0.01
NATIONAL	0.39	GENIKI	0.01
ILIOS	0.72	E.T.E.B.A	0.10
FINIX	0.29	EMPORIKI	0.04
NATIONAL INV CO	0.28	EPAG PISTEOS	0.003
HELLINIC INV CO	0.21	KRITIS	0.01
INV LEVEL FUND	0.21	MAKEDONIAS	0.003
ERGO INV	0.26	PIREOS	0.002
PISTEOS INV	0.35	ETHNIKI STE	0.05
IPIC INV	0.33	ETHNIKI KTIM	0.003

(Source: The Year Book of the A.S.E)

It seems again that the Greek investors failed to understand the above relationship of the Insurance firms with other firms listed in the A.S.E. or they have not discovered which stocks the Insurance firms hold in their portfolios.

For the causality which runs from the Banks to the Textile industry a possible explanation is that the Textile industries are financially related to the Banking sector. From the following table (Table 3) it is clear that the Textile Industry is the most heavily financed industry from the Banking sector in Greece.

TABLE 3.7

Banking credit to Industry by branch

Short term loans (in millions)

	Industries			
Year	Textile	Food	Chemicals	Steel
1982	77.616	55.480	22.932	25.764
1983	87.093	61.704	24.647	26.034
1984	100.909	71.414	27.452	33.041
1985	119.053	89.897	29.603	38.601
1986	103.989	93.806	30.834	42.840

(source:the monthly bulletin of the Bank of Greece)

Since I have examined in the first place the possibility for predictive interrelationships between the examined indices I will proceed and examine how, if at all, how these indices react to past available information other than the information which is contained in price histories.

5. Inflation as an Explanatory Variable when Testing the E.M.H

5.1 Theoretical Arguments

There has been agreement, some years ago, for the proposition that the rate of return on common stocks move directly with the rate of inflation. This proposition extends to rates of return for common stocks the Fisher hypothesis (1930), which states that expected rates of return consist of a real return plus expected inflation. Fisher's view is that the real and monetary sectors of an economy are largely independent. Thus the expected real return is determined by real factors and the expected real return and expected inflation rate are uncorrrelated. This assumption allows us to study asset-return inflation relationships without introducing a complete general equilibrium model for expected real returns, Fama and Schwert (1977).

According to theFisher Hypothesis, if the market is efficient or rational concerning the information available at time t-1, I_{t-1}, it will set the prices of the assets i.....j so that the expected nominal return on an asset, say j, from time t-1 to time t is the sum of the appropriate equilibrium expected real return and the best possible forecast of the expected inflation rate from t-1 to t.

$$E(R_{jt}/I_{t-1})=E(r_{jt}/I_{t-1})+E(IR/I_{t-1}) \qquad (1)$$

where Rjt is the nominal return on the asset j from t-1 to t, $E(r_{jt}/I_{t-1})$ the equilibrium real expected return for asset j implied by the information set I_{t-1} and $E(IR/I_{t-1})$

the best possible assessment of the expected value of inflation that can be made on the basis of I_{t-1}.

Given some measure for the expected inflation rate (IR/I_{t-1}) tests of the joint hypothesis that the market is efficient and that the expected real return of asset j and the expected inflation rate vary independently can be obtained from estimates of the regression model:

$$R_{jt}=a_j+b_jE(IR/I_{t-1})+\varepsilon_{jt} \qquad (2)$$

where bj should be close to unity, because such an estimate is consistent with the hypothesis that the real return on the asset j and the expected inflation rate are uncorrelated.

If someone is also interested in examining the relation of rates of return on the unanticipated part of inflation defined as $A(IR_t)-E(IR_t/I_{t-1})$, where $A(IR_t)$ the actual rate of inflation at time t, we can transform model (1) to the following one.

$$E(R_{jt}/I_{t-1})=E(r_{jt}/I_{t-1})+E(IR_t/I_{t-1})+[A(IR_t)-E(IR_t/I_{t-1})] \quad (3)$$

of which estimates can be obtained from the model:

$$R_{jt}=a_j+\beta_jE(IR_t/I_{t-1})+\gamma_j[A(IR_t)-E(IR_t/I_{t-1})]+u_{jt} \quad (4)$$

where an estimate of γ_j equal to one, will show that the nominal return on asset j varies in one to one relationship with the unexpected inflation rate.

When the expected part of inflation rate follows the one to one relationship with the rate of return of the asset j we say that the asset is a complete hedge against expected inflation in the sense that the expected real return on the asset is uncorreleted with the inflation. If the above relationship holds for the unexpected part of inflation rate then the asset is a complete hedge against unexpected inflation. Finally, if the above relationship holds for both the expected and unexpected parts of inflation then the asset is a complete hedge against inflation in the sense that the ex post real return on the asset is uncorrelated with the ex post inflation rate.

Although an asset can be a complete hedge against inflation β_j, γ_j=1, inflation can explain a small fraction on the variation in the assets nominal return, because non inflation factors can generate variations in nominal returns.

5.2 Stock Returns Reaction to Unexpected & Expected Inflation

The evidence, Branch (1974), Lintner (1975), Bodie (1976), Nelson (1976), Fama and Schwert (1977), presents a negative relationship between stock returns and both the anticipated and unanticipated parts of the inflation rate. For instance, Nelson (1976) using Scholes and S&P 500 stock market indices to measure the stock return and the Consumer Price Index (C.P.I) to measure inflation found a negative relationship between past and current unanticipated and anticipated parts of inflation rate with the stock returns, noting that the autocorrelation structure of the C.P.I he used would suggest apositive relationship between past inflation rates as a predictor of inflation.

According to the Nelson argument, if in a regression equation of the form $R_t=\alpha+\beta\rho_t$ where ρ_t is the inflation rate, we substitute the ρ_t with a past rate of inflation which contains no new information for the market to react to then the estimator of β will depend on the strength of correlation between the past rate of inflation and the expected rate of inflation at time t. Since this correlation should be positive in a highly correlated series such as the Inflation rate is in many countries, someone would expect the regression coefficients of the past rates of inflation to be positive.

In another study, Fama and Schwert (1977), using as the dependent variable the return from an equally weighted portfolio of N.Y.S.E stocks found that the expected U.S inflation is negatively related to the N.Y.S.E portfolio returns for the period 1953-71 and that only a small variation of the stock returns accounted for the relationship with inflation.

There have been offered many arguments for the negative effect of unanticipated inflation rate on stock returns and the most interesting of them are summarised below. Kessel and Alchian (1962) noted that unexpected inflation benefits net debtors and harms net creditors when contracts are written in nominal terms. The above net debtor net creditor hypothesis is very difficult to be tested since a firm may have long run contracts for different reasons e.g to purchase labour, raw materials as well as to borrow money to finance its operations. Thus is very difficult the examination of the above hypothesis without knowledge of the contractual obligations of firms.

Another explanation is that there are distributive tax effects as a result of unanticipated inflation, Lintner (1975). The argument is that since depreciation and inventory expenses are based on historical costs rather than current replacement costs, unexpected inflation which affects all prices simultaneously increases revenues without an offsetting increase in depreciation and inventory expenses thus increases the real tax burden of the firm.

In addition to the above arguments, unexpected increase in inflation could cause government policy makers to react by changing monetary or fiscal policy in order to counteract higher inflation. Such policy reactions, which can affect investments are probably the basis of the hypothesis that unexpected inflation is bad for business. For example, if high unexpected inflation increases the probability of price controls, then if price controls distort optimal production investment plans, they can have a negative effect on the value of firms, Schwert (1981).

Concerning the expected part of inflation, there has not been a satisfactory explanation for a possible negative relationship with the stock returns. One explanation is that higher inflation may lead to an increase in the variance of stockholders returns either because higher inflation leads to a greater relative price variability, or it is associated with more uncertain inflation, Pindyck (1984). The above model explains why unanticipated changes in inflation can lead to lower excess returns, for an unanticipated rise in inflation leads to a rise in volatility, which causes a fall in share prices now. However, if inflation and volatility are expected to remain higher thereafter, this leads to higher stock returns, so there is a positive relationship between the level of expected inflation and stock returns. Nevertheless, it has been argued, Attansio and Wadwani (1988) that if the market forms adaptive expectations instead of rational expectations and if one believes that higher inflation leads to higher risk, then under adaptive expectations lagged inflation will also reduce returns as investors take time to adjust their expectations. Such a proposition, the authors note, is very difficult to test.

Fama and Schwert (1977), in order to explain the observed negative relationship between stock returns and expected inflation, argued that some unidentified phenomenon might cause equilibrium expected returns of stocks to be negatively related to expected inflation rates or that the market may be inefficient in incorporating available information about future inflation into stock prices.

When testing the E.M.H with respect to an information set which contains past inflation rates a researcher is interested in two things: First, given that the expected inflation is measured correctly, the return on stocks, irrespective of the relationship positive or negative, should not react significantly to current or past expected inflation. Thus, in the following model,

$$R_t=\alpha_0 + \sum_{i=0}^{n} \beta_i E(IR_{t-i}/I_{t-i-1}) + u_t \qquad (5)$$

β_i should be equal to zero, for i=0 to n.

In an Efficient Market, as mentioned before, rational investors use all the relevant information dated at time t-1 in order to construct the expected Inflation for time t. Thus, in an Efficient market only the unanticipated part of Inflation really matters. An Efficient stock market now, should react only to the contemporaneous part of the unexpected inflation, since in such a market past rates of unanticipated Inflation have been embodied in the stock prices at the moment they were realized.

Thus, in the following model:

$$R_{tj}=a_0 + \sum_{i=0}^{n} \delta_i[A(IR_t)-E(IR_t/I_{t-1})] + u_t \qquad (6)$$

we should have that, $\delta_0=1$ and $\delta_i=0$, for i=1 to n.

Any unanticipated part of inflation which is not contemporaneous to the stock return should not prove to be statistically significant in the above regression. The opposite case would imply that the market is slow in incorporating available information into the prices, the existence of a potential trading rule and if the trading rule perform better than the Buy and Hold strategy violation of the Market Efficiency Hypothesis.

5.3 The Data

In order to examine the reaction of stock returns to inflation I measured inflation using the Consumer Price

Index. As already mentioned, when testing the Efficient Market Hypothesis with respect to information about inflation most researchers have tried to separate the expected from the unexpected part of Inflation. Then they test the joint hypothesis that the market is efficient and that the measure for the expected Inflation is correct. In such a case, evidence against the Efficient Market Hypothesis may imply that the market is indeed inefficient or the measure for the expected Inflation is incorrect.

Several methods have been proposed to separate the expected from the unexpected part of inflation. One way to separate the expected from the unexpected part of an economic variable like Inflation woul be to use statistical methods. The most commonly used statistical method is the Box-Jenkins ARIMA models. What is needed in these models is to obtain an appropriate representation of the Inflation series as a discrete linear stochastic process. When an appropriate model is obtained the error term of this model represents the unanticipated part of Inflation. By using this method someone is isolating the portion of any change which could not be predicted linearly from past rates of inflation. It would be easy to apply the Box-Jenkins technique, as in chapter one (ch 1), and separate the expected from the unexpected part of inflation. Nevertheless, for the case of Greece such a representation is not an adequate one since the government policy favoured price controls, 1983 and 1985. Under price controls the autocorrelation structure of the Inflation series may have changed and many large changes in the rate of Inflation could be anticipated to a considerable extent from changes in control regulations like progressive decontrol of some commodities.

Another method commonly used is the survey forecast method. This method is based upon a formal statistical survey among market participants. The market participants are chosen on a random basis or on the basis of importance. The theoretical argument behind the survey method is that the forecasts published by these market participants correspond to the market forecasts since other market participants base their investment policy on those public available forecasts. *"The main merit of the survey is perhaps that the market participants themselves are prepared to accept the data as being an adequate reflection of their expectations"*, Gowland (1986). It is argued though at this point, that it is likely the expectations of which the response to a survey is based are not the responses on which trading decisions are made. Additionally, forecasts based on survey data fail frequently to satisfy the assumption of rational forecasts, Maddala (1989), although some studies give evidence for rationality, Lai (1990).

A Cost-Benefit argument might explain why some survey expectations data fail statistical tests for rationality. The argument is that it may happen that most of the respondents must have little incentive to produce good forecasts, the respondents may have no risk of loss of reputation since individual forecasts are not published, Thus, when they form their forecasts the survey respondents do not have incentives to put much effort and use all the relevant available information. Finally, Figlewski and Wachtel (1981), point out another source for the observed bias in the surney forecasts, this one arising from aggregation over individuals. The argument is that if only the mean response of a number of individuals are considered, the rationality of the mean response may be unrelated to the rationality of individual responses. The survey mean may not be a rational forecast even when all the individual forecasts are rational. When the above authors when analyzed the Livingston data, probably the most well known data set on price expectations, they reject statistically the rationality assumption. For the case of Greece survey data are not available since there are not any market agents who publish their forecasts.

Another method to separate the expected from the unexpected part of inflation, is to use as a proxy for the expected Inflation rate at time t the short term interest rate on Treasury Bills for time t, Fama (1975), Nelson and Schwert (1977). In this a case a regression of the Inflation rate on the Treasury Bill rate,

$$IR_t=\alpha + \beta TB_t+u_t \qquad (7)$$

should yield a βo coefficient statistically significant and close to unity. Thus when the interest rate on a Treasury Bill which matures at the end of period t is used as a proxy for the expected Inflation rate for period t, the unexpected inflation rate is measured as the difference between the Inflation rate realised ex post and the ex ante interest rate. For the case of Greece the minimum period for holding a Treasury Bill is three months, and these Treasury Bills were not available to the public until 1987. Additionally, the rate on these certicicates was determined by the Central Bank and did not follow some relationship with inflation. Thus, there are reasons to believe that the Treasury Bill rate might not be an adequate proxy for the expected Inflation rate in this study.

Finally, when someone does not separate with the above methods the expected from the unexpected part of inflation, then direct tests for the Efficient Market Hypothesis can be performed by examining if past rates of inflation can be used succesfully as explanatory variable in order to forecast the current stock return.[3] In an efficient market past information either expected or unexpected has been reflected on stock prices and thus should be proved insignificant in a predictive model for stock returns (see ch.1 section 2.2.1).

5.4 Cointegration anlysis

In my analysis as a first step I will investigate if there is any predictive long run relationship between stock returns and inflation using again the consept of cointegration. As already known, when two series are cointegrated then Granger causality runs at least in one direction. Since both C.P.I index and the stock market indices are integrated of order one, as the appropriate test for integration indicated, the cointegration regression has the form:

$$I_{jt}=a+b\ CPI_t+u_t \qquad (8)$$

In the above regression I used the Sargan Bhargava Durbin Watson statistic and the Augmented Dickey Fuller test in order to investigate if the residual series of the above regression is integrated of order zero, as is demanded for cointegration to hold.

From the cointegration tests I obtained the following results:

Variables	Cointegration Statistics	
	CRDW	ADF statistic
Banks Inflation	0.11	-0.88
Insurance Firms Inflation	0.42	-1.42
Textile Ind Inflation	0.18	-0.85
Food Ind Inflation	0.12	-1.11
Miscellaneous Firms Inflation	0.12	-0.88
Building Constr Inflation	0.08	-0.85
Chemicals Inflation	0.14	-0.82
Steel Ind Inflation	0.04	-0.40

From the above results we can see that in almost all cases the Durbin Watson statistic is lower than the critical value indicating that the null hypothesis of no cointegration has to be accepted at 1%, 5% and 10% signifivcance levels. For the case of the Insurance index the Durbin Watson statistic indicated cointegration at 5% significance level. Nevertheless, the Augmented Dickey Fuller statistic, as a more robust indicator for cointegration, lead me to accept the hypothesis of no cointegration for all the examined cases. In addition to the above results there were no Error Correction Model which would imply cointegration i.e., an Error Correction Model with statistically significant Error Correction Term. Thus from the cointegration analysis I have to conclude that there is no any long run predictive relationship between C.P.I. and stock prices.

5.5 Granger causality tests

In order to examine the reaction of the stock market indices to the short run dynamics of inflation I used again the Granger causality test. I regressed the return of stocks on its past values and lagged values of the inflation rate to see if stock returns can be forecast by the use of past values of inflation rate.

From the Granger causality tests I obtained the following results:

TABLE 3.8

Variables		F statistics		Causality
Banks	Inflation	$F_1=1.39$	$F_2=0.87$	———
Insurance	Inflation	$F_1=1.83$	$F_2=0.77$	———
Textile	Inflation	$F_1=0.99$	$F_2=0.61$	———
Food Ind	Inflation	$F_1=1.26$	$F_2=0.86$	———
Miscellan	Inflation	$F_1=0.76$	$F_2=0.47$	———
Building	Inflation	$F_1=0.87$	$F_2=0.58$	———
Chemicals	Inflation	$F_1=1.41$	$F_2=0.36$	———
Steel Ind	Inflation	$F_1=0.71$	$F_2=1.39$	———

Where F_1 refers to the regression where the stock return is the dependent variable and F_2 in the regression where the inflation rate is the dependent variable.

As the above table indicates, there is no short-run temporal predictive relationship between inflation and stock returns. In all caces the calculated F statistics are less than the critical values. The F statistics when the return was the depedend variable were much higher than the case when the inflation rate was the depedend variable indicating that inflation rate leads stock returns but this leading retlationship was not statistically significant. It is interesting to note here that the higher F statistics was obtaind for the case of the Insurance sector of the Athens Stock Exchange, but again the statistic was not greater than the critical value.

5.6 Regression analysis

As explained before (ch 2) the Granger Causality test examines the overall effect of past explanatory variables on the dependent variable. In order to focus on the effect of every single explanatory variable on the dependent variable I used regression analysis and I regressed the return on stocks on six lags of the inflation rate.

$$R_{jt} = \beta_0 + \sum_{i=1}^{6} \beta_j \; IR_{t-1} + u_t \qquad (9)$$

and test if $IR_{t-1}=IR_{t-2}=....=IR_{t-6}=0$

and $IR_{t-1}=0,\ IR_{t-2}=0, ...IR_{t-6}=0$

From the above type of regression I obtained the following results:

TABLE 3.9

O.L.S Results

Variables	Banks Estim.	Banks "t"	Insurance Estim.	Insurance "t"	Building Estim.	Building "t"
Constant	0.01	0.63	0.06	1.81	0.04	1.16
IR_{t-1}	-1.00	1.42	-1.32	1.35	-1.82	1.67
IR_{t-2}	-0.45	0.64	-1.88	1.91	-0.82	0.75
IR_{t-3}	-0.74	1.05	-1.40	1.42	-0.68	0.62
IR_{t-4}	1.28	1.83	1.96	2.02	1.72	1.59
IR_{t-5}	0.34	0.48	-1.09	1.09	-1.28	1.15
IR_{t-6}	0.41	0.59	0.44	0.46	0.05	0.04
	R^2=0.11	F=1.85	R^2=0.15	F =2.8	R^2=0.08	F=1.3
	DW=1.16		DW=1.52		DW=1.41	

Variables	Chemicals Estim.	Chemicals "t"	Miscellan. Estim.	Miscellan. "t"	Food Ind Estim.	Food Ind "t"
Constant	0.05	1.34	0.04	1.93	0.11	2.23
IR_{t-1}	-1.85	1.88	-0.71	1.11	-2.27	1.71
IR_{t-2}	0.36	0.36	-0.67	1.03	-1.45	1.08
IR_{t-3}	-2.02	2.03	-0.78	1.21	-1.34	1.00
IR_{t-4}	1.18	1.21	0.39	0.62	0.39	0.29
IR_{t-5}	1.91	1.90	-0.40	0.61	-0.45	0.33
IR_{t-6}	1.48	1.52	0.17	0.28	-0.08	0.66
	R^2=0.08	F=1.31	R^2=0.05	F =0.8	R^2=0.06	F=1.0
	DW=1.37		DW=1.41		DW=0.86	

	Textiles		Steel Ind.	
Variables	Estim.	"t"	Estim.	"t"
Constant	0.04	1.11	0.04	1.74
IR_{t-1}	-1.28	1.25	-1.54	2.34
IR_{t-2}	-0.16	0.15	-0.18	0.28
IR_{t-3}	-1.74	1.69	-0.71	1.08
IR_{t-4}	1.80	1.77	0.65	1.01
IR_{t-5}	-0.59	0.57	-0.69	1.04
IR_{t-6}	0.50	0.50	0.23	0.36
	R^2=0.07	F=1.16	R^2=0.07	F =1.21
	DW=1.22		DW=1.63	

where "t" are the absolute t ratios and DW the Darbin Watson statistic.

From the above results we can see that the higher, although not impressive, R^2 as an overall measure of the explanatory power exists for the Banking and the Insurance sectors. The F statistic for the Insurance sector is higher than the critical value and for the Banking sector less than the critical value but relatively high in comparison to the other sectors. Nevertheless, in all the above models the D.W. statistic was very low indicating significant positive autocorrelation in the disturbance term of the above regressions, thus making the obtained statistics invalid.

In order to avoid the autocorrelation problem, and assuming correct specification of the dynamics in the above equations, I reestimated the models by using the Cochrane-Orcutt estimation method[4]. From the C-O method I obtained the following results:

TABLE 3.10

Cochrane-Orcutt Results

Variables	Banks Estim.	Banks "t"	Insurance Estim.	Insurance "t"	Building Estim.	Building "t"
Constant	0.02	0.71	0.06	1.56	0.03	0.69
IR_{t-1}	-1.31	2.02	-1.48	1.53	-1.53	1.74
IR_{t-2}	-0.51	0.78	-1.86	1.99	-0.72	0.70
IR_{t-3}	-0.89	1.36	-1.46	1.56	-0.56	0.55
IR_{t-4}	1.27	1.97	2.01	2.17	1.77	1.74
IR_{t-5}	0.21	0.33	-1.15	1.22	-1.14	1.10
IR_{t-6}	0.39	0.60	0.48	0.51	0.22	0.21
	W=12.8		W=18.19		W=7.84	

Variables	Chemicals Estim.	Chemicals "t"	Miscellan. Estim.	Miscellan. "t"	Food Ind Estim.	Food Ind "t"
Constant	0.05	1.06	0.05	1.79	0.14	1.94
IR_{t-1}	-1.84	1.96	-1.00	1.64	-2.77	2.45
IR_{t-2}	-0.34	0.37	-0.69	1.13	-1.74	1.56
IR_{t-3}	-1.99	2.15	-0.90	1.48	-1.61	1.38
IR_{t-4}	1.16	1.26	0.39	0.65	0.01	0.01
IR_{t-5}	-1.90	2.04	-0.51	0.84	-0.80	0.70
IR_{t-6}	1.41	1.52	0.13	0.22	-0.70	0.62
	W=10.83		W=6.05		W=7.71	

	Textiles		Steel Ind.	
Variables	Estim.	"t"	Estim.	"t"
Constant	0.05	1.00	0.04	1.46
IR_{t-1}	-1.04	1.72	-1.57	2.45
IR_{t-2}	-0.25	0.26	-0.13	0.21
IR_{t-3}	-1.89	1.99	-0.73	1.16
IR_{t-4}	1.76	1.87	0.69	1.11
IR_{t-5}	-0.75	0.79	-0.71	1.14
IR_{t-6}	0.36	0.39	0.33	0.52
	W=10.67		W=7.61	

Where W is the Wald statistc which tests the hypothesis $IR_{t-1}=IR_{t-1}=....IR_{t-6}=0$.

The most important result from the above regressions is that several lagged inflation rates appeared to be individually significant with the first lag prominent as a common significant lag in many cases. The significance of the first lag implies market inefficiency irrespectivelly of the announcement day of the inflation rate.

If the announcement of Inflation for the period t-i is made near the end of period t-i, it implies that the market is slow in incorporating information instantaneously and thus is inefficient. On the other hand, if the announcement for period t-i is made at the beginning of period t-i+1 the market is again inefficient in the following sense: The C.P.I. is not an end of the month index but data are gathered during the whole period in question. The market by reacting to the announcement of inflation means that it was inefficient in incorporating information about inflation during the period when inflation was sampled (diagram 1).

<u>DIAGRAM 1</u>

Time t   Time t-1

R_t ____________________ I_{t-1} | R_{t-1} ____________________

$I_t, \ldots\ldots\ldots, I_{t-29}, I_{t-30} \ldots I_{t-1}, \ldots\ldots\ldots, I_{t-1-29}, I_{t-1-30}$

$I_t = f(I_{t-30}, I_{t-29} \ldots, I_t)$ $\quad$ $I_{t-1} = f(I_{t-1-30}, I_{t-1-29}, \ldots I_{t-1})$

In the above diagram, the dependent variable of the model, the stock return, R_t, refers to the end of period t. The Inflation rate I_{t-1} is announced at the beginning of period t but refers to period t-1. The inflation I_{t-1} is a function of observations I_{t-1-30}, $I_{t-1-29}, \ldots\ldots I_{t-1}$, that is it is not an end of the month Index. In an Efficient Market the return R_{t-1} should react to the inflation I_{t-1} and not the return R_t. Instead the return Rt should react to inflation It which is a function of the observations I_{t-30}, I_{t-29}, ... I_t. This is not true in the Athens Stock Exchange, implying thus market inefficiency.

From the above tests which investigate if there is any predictive relationship between stock returns and inflation rate I have to conclude that such a relationship does not exist either in the long run, cointegration results, or in the short run, Granger causality results. A possible evidence against the Efficient Market Hypothesis is that in the regression analysis some past inflation rates appeared individually to influence statistically the current stock return.

In the following analysis I will investigate whether more Macroeconomic variables which theoretically affect stock returns have any predictive value. In the first place I will investigate the Market Efficiency with respect to an information set which includes every variable separately. Then the information set will be enlarged to include all the examined explanatory variables in order to examine the joint influence of individual significant lags, if these exist for other variables as in the case of the inflation rate.

6. Money Supply as an Explanatory Variable when Testing the E.M.H

6.1 Theoretical Arguments

The relation of money to stock prices has been the subject of academic research for many years and there is considerable agreement among economists that changes in the quantity of money have important influences on the movement of stock prices.

In the empirical analysis which will follow, given the importance of money supply changes in the determination of stock prices, the question is how efficiently the stock market participants incorporate the information contained in the money supply changes into stock prices. My purpose is to examine again if there is any predictive relationship between stock returns and past changes in money supply.

There have been offered many explanations about the relationship of money supply and stock prices. In the following part I will try to summarize the most important of them. Beginning with the early work of Sprinkel (1964), several studies have attempted to exploit statistically the reaction of the stock market to changes in themoney supply. The stock market-money supply relationship has been widely tested because of the belief that money supply changes have important direct effects though portfolio changes, and indirect effects through their effect on real activity variables which are in turn postulated to be fundamental determinants of stock prices.

Past studies which used the monetary portfolio model (M.P) developed by Friedman (1961), Friedman and Schwartz (1963) and others assumed that investors reach an equilibrium position in which, in general they hold a number of assets including money in their portfolio of assets. A monetary disturbance such as an unexpected increase or decrease in the growth rate of the money supply causes disequilibrium in asset portfolios by making actual money balances depart from desired money balances. The attempt by investors as a group to attain their desired money positions then transmits the monetary change to markets at large. Investors respond to the wealth effect of increased money growth by exchanging money for a variety of assets in asset markets like short and long term bonds, stocks, real estate, durable goods, capital goods and human capital.

Hamburger and Kochin (1972), argued that *"money stock is itself an asset in a portfolio of wealthholders. Increases in the stock of money will cause decreases to the benefits of holders from the last dollar of money held. Changes in the supply of money are therefore a proxy for changes in the return of money"*. They also argued that return on corporate stock will be among *"the first and most strongly affected"* by changes in the money supply since its holders *"institutions dealers and wealthy individuals who hold the bulk of the floating supply of corporate stock are among the most responsive to changes in their money balances"*

Hamburger and Kochin also argued that changes in the money supply affect corporate earnings. The explanation is based on the Hypothesis that the money supply announcements provide information about future money demand. For the link to operate, money demand must depend on expected future output , as well as current output. Empirical studies, Fama (1982), have shown than when future and current income are included in the money demand function, future income is highly significant, when the actual future output serves as a proxy for the expected future output.

If money demand depends on expected future output, then market participants cannot determine aggregate money demand because they do not know other market participants' expectations. In that sense, money supply announcements provide information about expected future output. For example, an unanticipated increase in the money stock tells agents that aggregate money demand is greater than they forecast. On the basis of this information, estimates of the real future activity rise. With higher expected future output the real rate must rise to clear the market for consumption and investment. Information which causes agents to revise upwards their forecasts of future real activity should cause stock prices to rise. Though the discount rate will rise to reflect the higher ex ante real rate, it is argued that the increase is more than offset by the growth of expected corporate cash flow, and this is because the reason for the higher real rate is an expected increase in the output.

Another channel by which money supply may affect stock prices is through expected inflation. An unanticipated increase in money supply affects interest rates and leads to higher expected inflation. As already noted the relationship between stock prices and expected inflation is not a straightforward one. Also, Summers (1981), argued that increased expected inflation raises the return on alternative assets like property and thus depress stock prices.

An alternative explanation of the response of stock prices to unexpected changes in the money supply is based on investors expectations of the reaction of the authorities to the surprise, this scenario isknown as the "policy anticipation effect". In particular, an unexpected jump in money stock will lead market participants to believe that the authorities will have to tighten credit to offset the rise. The measures taken by the authorities will involve higher interest rates, Gowland (1986). This will lead to lower stock prices for two reasons: First, the discount rate will rise to reflect the higher rates. Secondly, expected corporate cash flows will decline if market participants believe that an increase in rates depresses economic activity.

An additional explanation offered for the effect of money supply on stock prices is through the risk premium. An asset has a risk premium to the extent that it contributes to the variation of the holders total portfolio. The major determinant of an asset riskiness is not the variance in its returns but the covariance of the asset return with the returns of other assets. Portfolio theory suggests that changes in the stock market produce greater risk, the more they coincide with variations in other sources of income and the larger the fluctuation in the other sources. Movements in thisstock market caused by money are likely to coincide with fluctuations in the other assets of the portfolio. Therefore changes in the value of equities caused by movements in the supply of money are likely to be potent marginal contributors to the risk premium demanded by holders of equities. As the variability of money rises so does the variability of the economy, the risk premium rises and stock prices fall since:

$$P_t=\sum_{0}^{\infty}\frac{E_t}{(1+i_t+r_t)^t}$$

where E_t the expected (unaffected) earnings at time t, i_t the risk free rate at time t and r_t the risk premium at time t.

Finally,the money supply can affect stock prices as a sunspot in the sense of an unjustified arbitrary belief. Camerer (1989) refers to the sunspot explanation of money supply *"Traders often say that they know these announcements,* (money supply announcements), *contain no information, but they expect them to affect prices, and their belief is self fulfilled"*. Of course the sunspot effect on stock prices can apply to variables otherthan the money supply. Thus, every variable in this study which is supposed to affect stock returns can be interpreted as a sunspot as well.

When testing the Efficient Market Hypothesis, we are interested in examining if past innovations in money supply result in stock price changes. In an Efficient Market, past changes in money supply measures should not have any predictive value in a model where the dependent variable is the stock return. Empirical studies of the relationship between money supply and stock prices, as already mentioned, have concluded that monetary variables do result in stock price changes. I have to mention here that there are some researchers though who challenge the above point of view; for example, Cutler, Porteba and Summers (1989), by using VAR (Vector Autoregression Analysis), conclude that money supply as an explanatory variable among other macroeconomic variables, fail to explain return variations in their sample. For the Efficient Market Hypothesis, the results are much more contradictory.

In an early work, Sprinkel (1964), based on graphical analysis of peaks and troughs, concludes that changes in stock prices lag behind changes in growth rates of money supply. His trading rule based on the above lagging relationship between money supply and stock prices outperformed the naive Buy and Hold strategy giving evidence against the Efficient Market Hypothesis. Additionally, Reily and Lewis (1971), by performing regression analysis, conclude that their results are consistent with Sprinkel's results. They observed that, *"major and sustained declines in the growth rate of money supply are followed by stock market declines but false signals are possible"*. Also, Hamburger and Kochin (1972), in their study indicate a substantial relationship between stock price changes and changes in money growth rates, and they recognise the potential use of the equation as a trading rule.

On the other hand, Kraft and Kraft (1977), by using causality tests, conclude that *"stock price measures lead than lag monetary actions"* giving thus evidence in favour of the Efficient Market Hypothesis. Pearce and Roley (1983), also give evidence for Market Efficiency, since their results indicate that stock prices react to the unanticipated part of money surprises and that the reaction is immediate. In another causality test based study, Morkerjee (1987), making international comparisons concluded that the Efficient Market Hypothesis stands as a valid Hypothesis for U.S.A and U.K markets but not for other countries. Finally, supportive evidence for the Efficient Market Hypothesis is given by Hashmzadeh and Taylor (1988) based on Granger Simms causality tests.

7. Other Explanatory Variables for Testing the Efficient Market Hypothesis in the A.S.E.

In the information set which I will use to test the Efficient Market Hypothesis, except inflation rates and money supply I will include the exchange rate U.S dollar/Drachmae, the gold price, and the Interest rates of the Central Bank certificates specifically for the case of the Banking sector.

Of particular interest is the exchange rate. Exchange risk may affect firms capital positions, when these firms are involved in foreign markets in a variety of ways. Exchange rate movements can greatly affect the market value of firms overseas assets or liabilities and cause fluctuations in firm's capital positions.

Some fluctuations in firms capital due to foreign exchange rate movements can be offset somewhat by relative changes in the aggregate price levels; however, there is evidence that deviations from Purchasing Power Parity (P.P.P.) in the short run are substantial and not necessarily self-correcting, Adler and Dumas (1980).

Fluctuations in the value of assets and liabilities that result from changes in exchange rates may expose firms to substantial risks, if firms are not properly hedged. While a variety of well known mechanisms exists for hedging the exposure to exchange rate risk, the extent to which firms effectively utilise these mechanisms remains a question.

Firms can hedge exchange rate risk by matching the currency denominations of their assets and liabilities or by using the exchange rate futures and options markets. However, these strategies may not be costless, and firms may choose to suffer some degree of exposure. Also, some firms, especially banks, may expose themselves to exchange rate risk to speculate on exchange rate movements in their trading room activities. The large value of foreign exchange trading makes large profits or losses possible from even small movements in exchange rates.

The Central Bank certificate interest rate is an important variable for the case of the Banking sector.

Commercial Banks, according to the Central Bank legislation are obliged to buy with a substantial part of their deposits certificates from the Central Bank. These certificates are kept by the Commercial Banks until the expiry day. Changes in the certificate rate thus, may directly influence the profits of the Commercial Banks. These certificates were not open to the public until 1987.

Finally, the common belief of Greek investors that gold is a "good" investment and they hold in their portfolio gold or gold sovereigns led me to include gold prices as an additional explanatory variable. Note here, that in addition to the gold price , foreign exchange rates may have indirect effects on stock returns through portfolio adjustments.

8. Econometric Analysis

In order to examine in thefirst place, any possible relationship between the returns of the examined indices and the proposed explanatory variables in high and low frequencies I used Granger-Causality tests and cointegration analysis as described before.

Since cointegration analysis and the Granger causality tests require stationary series, I used the Augmented Dickey-Fuller test to assess the degree of integration of the proposed explanatory variables, i.e., how many times they have to be differenced to produce stationarity. As the following results suggest, the proposed variables are first difference stationary, that is they are integrated of order one.

Variable	A.D.F test statistic Levels	First differences
M1	-1.32	-3.41
M3	0.98	-2.87
Central Bank rate	-2.86	-3.65
Gold price	-1.51	-4.49
U.S dollar price	-1.79	-3.65

In my analysis the measures of money supply which I will use are both M1 and M3 because there is no a priori evidence about which measure of the money supply stock market participants view as the more accurate proxy to gauge the monetary policy actions of the authorities.

8.1 Granger causality tests

Thus, in order to perform the Granger causality test I used first difference transformations of the proposed variables. For the Granger causality test I used again twelve lags of the dependent and explanatory variables, since my observations are monthly and twelve lags are suggested by the econometric theory in the case of monthly observations. The Granger causality tests include only lagged variables because as mentioned before Instataneous causality tests do not allow us to evaluate the efficient market hypothesis since according to the efficient market hypothesis the market at time t is expected to react to contemporaneous macroeconomic information.

From the Granger causality tests I obtained the following results:

TABLE 3.11

Variables		F statistic		Causality
BANKS	M1	$F_1=1.10$	$F_2=0.80$	———
BANKS	M3	$F_1=1.51$	$F_2=1.14$	———
BANKS	Gold	$F_1=0.42$	$F_2=0.49$	———
BANKS	Exch. Rate	$F_1=1.63$	$F_2=0.75$	———
BANKS	Cert Rate	$F_1=0.98$	$F_2=0.75$	———

Variables		F statistic		Causality
INSURANCE	M1	$F_1=0.72$	$F_2=1.21$	———
INSURANCE	M3	$F_1=1.36$	$F_2=0.55$	———
INSURANCE	Gold	$F_1=0.66$	$F_2=0.74$	———
INSURANCE	Exch. Rate	$F_1=0.64$	$F_2=0.66$	———

Variables		F statistic		Causality
TEXTILES	M1	$F_1=0.57$	$F_2=0.51$	———
TEXTILES	M3	$F_1=1.32$	$F_2=0.87$	———
TEXTILES	Exch. Rate	$F_1=1.60$	$F_2=1.03$	———
TEXTILES	Gold	$F_1=0.73$	$F_2=0.54$	———

Variables		F statistic		Causality
STEEL IND.	M1	$F_1=0.53$	$F_2=0.47$	———
STEEL IND.	M3	$F_1=0.81$	$F_2=1.08$	———
STEEL IND.	Exch. Rate	$F_1=1.95$	$F_2=1.13$	———
STEEL IND.	Gold	$F_1=0.73$	$F_2=0.54$	———

Variables		F statistic		Causality
MISCELLANEOUS	M1	F=1.08	F_2=0.57	———
MISCELLANEOUS	M3	F_1=1.71	F_2=0.73	———
MISCELLANEOUS	Exch. Rate	F_1=1.64	F_2=0.70	———
MISCELLANEOUS	Gold	F_1=1.25	F_2=0.56	———

Variables		F statistic		Causality
FOOD IND.	M1	F_1=0.49	F_2=0.81	———
FOOD IND.	M3	F_1=1.03	F_2=0.74	———
FOOD IND.	Exch. Rate	F_1=1.75	F_2=0.62	———
FOOD IND.	Gold	F_1=0.57	F_2=0.22	———

Variables		F statistic		Causality
CHEMICALS	M1	F_1=0.78	F_2=0.55	———
CHEMICALS	M3	F_1=1.15	F_2=0.62	———
CHEMICALS	Exch. Rate	F_1=1.24	F_2=0.75	———
CHEMICALS	Gold	F_1=0.52	F_2=0.49	———

Variables		F statistic		Causality
BUILDING	M1	F_1=0.56	F_2=0.63	———
BUILDING	M3	F_1=1.06	F_2=1.00	———
BUILDING	Exch. Rate	F_1=1.67	F_2=0.81	———
BUILDING	Gold	F_1=0.42	F_2=0.70	———

From the above results it seems that there is no any significant Granger causality between the examined variables. Nevertheless, individual significant lags appeared again especially for the Banking sector, as in the case when the inflation rate was the explanatory variable.

8.2 Cointegration analysis

In order to assess possible causalities in low frequencies I used cointegration analysis. Since the index price levels and the levels of the proposed variables are integrated of order one the cointegration regression takes the usual form:

$$Y_t=\alpha+\beta X_t+z_t$$

and for cointegration to hold $\hat{z}_t$ must be integrated of order zero. Applying the Sargan Bhargava Durbin Watson test and the Augmented Dickey-fuller test on the estimated residuals I obtained the following results:

TABLE 3.12

COINTEGRATION RESULTS: Banks

Variables		Cointegration statistics	
		CRDW	ADF
Banks	M3	0.15	-1.28
Banks	M1	0.17	-1.22
Banks	Exch Rate	0.06	-0.85
Banks	Cert Rates	0.06	-0.75
Banks	Gold	0.19	-1.49

COINTEGRATION RESULTS: Insurance firms

Variables		Cointegration statistics	
		CRDW	ADF
Insurance	M3	0.35	-2.08
Insurance	M1	0.39	-1.99
Insurance	Exch Rate	0.22	-1.17
Insurance	Gold	0.49	-2.17

COINTEGRATION RESULTS: Textiles

Variables		Cointegration statistics	
		CRDW	ADF
Textiles	M3	0.21	-1.12
Textiles	M1	0.22	-1.13
Textiles	Exch Rate	0.11	-0.78
Textiles	Gold	0.25	-1.29

COINTEGRATION RESULTS: Chemicals

Variables		Cointegration statistics	
		CRDW	ADF
Chemicals	M3	0.16	-1.13
Chemicals	M1	0.16	-1.11
Chemicals	Exch Rate	0.12	-0.77
Chemicals	Gold	0.15	-0.99

COINTEGRATION RESULTS: Building construction

Variables		Cointegration statistics CRDW	ADF
Building Con	M3	0.08	-1.45
Building Con	M1	0.08	-1.40
Building Con	Exch Rate	0.09	-0.93
Building Con	Gold	0.08	-1.21

COINTEGRATION RESULTS: Food industry

Variables		Cointegration statistics CRDW	ADF
Food Ind	M3	0.16	-1.91
Food Ind	M1	0.17	-1.77
Food Ind	Exch Rate	0.07	-0.91
Food Ind	Gold	0.21	-1.87

COINTEGRATION RESULTS: Miscellaneous firms

Variables		Cointegration statistics CRDW	ADF
Miscellaneous	M3	0.18	-1.35
Miscellaneous	M1	0.22	-1.25
Miscellaneous	Exch Rate	0.06	-0.45
Miscellaneous	Gold	0.25	-1.56

COINTEGRATION RESULTS: Steel industry

Variables			Cointegration statistics	
			CRDW	ADF
Steel	Ind	M3	0.05	-1.03
Steel	Ind	M1	0.05	-1.03
Steel	Ind	Exch Rate	0.02	-1.05
Steel	Ind	Gold	0.09	-0.86

From the above results we can comment that the Durbin Watson statistic leads to acceptance of the null hypothesis of no cointegration in all cases, except of the case of the Insurance sector where the D.W statistic indicated cointegration between the pairs Insurance index-M1 at 10% significance level and Insurance index-M3, Insurance index-gold price at 5% significance level. Nevertheless, the Augmented Dickey Fuller test which is more robust test for cointegration rejects strongly the Hypothesis of cointegration in all cases. As additional evidence of no cointegration, the error correction term in the error correction models of the above possibly cointegrated pairs appeared to be insignificant.

From the above results I have to conclude that the Efficient Market Hypothesis stands as a valid Hypothesis for the examined stock market indices with respect to the information sets: I_{t-1}=(inflation rates,$_{t-1}$), I_{t-1}=(money supply,$_{t-1}$), I_{t-1}=(gold prices,$_{t-1}$), I_{t-1}=(foreign exchange rates,$_{t-1}$), I_{t-1}=(Central Bank Certificate rate,$_{t-1}$), even when in the above information sets I include the Error

Correction terms from the cointegrating regressions.

Nevertheless, since individual lags in some cases appeared statistically significant in explaining stock returns, I would like to test if the Market Efficiency holds with respect to the information set I_{t-1}=(inflation rates,$_{t-1}$, money supply,$_{t-1}$, gold prices,$_{t-1}$, foreign exchange rates,$_{t-1}$, Central Bank Certificate Rates,$_{t-1}$), because probably the combined effect of the significant individual lags of the explanatory variables may yield a valid predictive model for stock returns.

8.3 Multiple Regression Analysis

The analytic way the proposed variables may influence the stock returns will be investigated with multiple regression analysis. In order to perform multiple regression analysis and test the validity of the Efficient market Hypothesis, with respect to the new expanded information set, I used the following alternative model[5]:

$$R_{tj}=\alpha_1(L)MS_{t-1}+\alpha_2(L)CB_{t-1}+\alpha_3(L)I_{t-1}+\alpha_5(L)G_{t-1}+\alpha_5(L)ER_{t-1}+u_t$$

with $\alpha_1=\alpha_2=\alpha_3=\alpha_4=\alpha_5=0$ for the Efficient Market Hypothesis to hold.

In the above model $\alpha_j(L)$ represents the lag polynomial, R_t is the stock return of index j, MS is changes in the broad measure of money supply, CB the change in the rate of the Central Bank Certificates, I is inflation rate, G is the rate of change of the gold price, ER the rate of change of the U.S dollar price and u_t the error term. All variables in the above model are integrated of order zero, I(0), so no econometric problems arise from the model specification.

Note that the lags, as already mentioned, refer to the announcement day, since it is possible a variable which refers to time t-1 to be announced at time t. In such a case the variable which refers to t-1 may influence the stock return but the market efficiency will not be violated since the variables are in fact contemporaneous.

In order to find the appropriate model, two procedures have been proposed in the Econometric literature. The specific to general method starts with a simple model and then the model is extended by putting in all the statistically significant variables and stopping at the point where a variable proves to be statistically insignificant. This method suffers from several econometric drawbacks as Hendry (1979) noted. Thus, I chose the Hendry's approach which is called Top-Down or General to Specific approach. This method starts with a general dynamic model which is overparametrised and then the model is simplified with a sequence of simplification tests.

Following Hendry's method I noticed that all overparametrised models (which do not include dynamics of the depedend variable) had the common characteristic of a low Durbin Watson statistic thus indicating significant positive autocorrelation. This problem of autocorrelation, has been encountered before when I tried to exploit individual significant lags of inflation rates which could help predict stock returns. In order to avoid the autocorrelation problem at that stage, I followed the C-O estimation method making the assumption that the autocorrelation was due to omitted explanatory variables (other than the dynamics of the depedend variable) that the error term captures. But what one can say for the overparametrised models which included several lags of not only one but many explanatory variables.

8.3.1 <u>Mispecified Dynamics</u>

Sargan (1964), and Hendry & Mizon (1978), pointed out that a significant D.W statistic may imply that we have a serial correlation problem due to misspecified dynamics. Consider the model:

$$Y_t=\beta X_t+u_t \quad (1) \quad \text{with} \quad u_t=\rho u_{t-1}+\varepsilon_t$$

where ε_t are independent and have a common variance σ^2. Then we can write (1) as

$$Y_t=\rho Y_{t-1}+\beta X_t-\beta\rho X_{t-1}+\varepsilon_t \quad (2)$$

Which has the form of the stable dynamic model:

$$Y_t=\beta_1 Y_{t-1}+\beta_2 X_t+\beta_3 X_{t-1} \qquad \text{where } |\beta_1|<1,$$

A test for $\rho=0$ is a test for $\beta_1=0$ (and $\beta_3=0$) if the test is rejected then the serial correlation tests in (1) may be due to "mispecified dynamics", that is the omission of the variables Y_{t-1} and X_{t-1} from the original equation. The models which I tested included dynamics of the explanatory variables, thus the misspecified dynamics problem may be due tothe omission of lagged dependent variables. In an Efficient market past returns should not prove to be significant in explaining the current return, since in such a market returns are serially uncorrelated.

A.C.F of returns

Lags	Banks	Insurance	Textiles	Steel ind
1	0.40*	0.21*	0.26*	0.22*
2	0.10	-0.19	0.41*	-0.01
3	-0.06	-0.07	0.25*	0.00
4	-0.08	-0.12	0.10	0.46*
5	0.12	0.00	0.08	0.33*
6	0.25*	0.08	-0.01	-0.03
7	0.41*	0.06	0.21	-0.03
8	0.13	-0.02	0.02	0.00
9	-0.08	-0.06	0.05	0.07
10	-0.14	-0.08	0.00	-0.08
11	-0.09	-0.02	0.01	-0.02
12	0.11	0.10	0.00	-0.03

Lags	Food Ind	Chemicals	Building C	Miscellaneous
1	0.55*	0.26*	0.29*	0.27*
2	0.27*	0.07	0.09	0.08
3	0.12	-0.04	0.07	-0.07
4	0.19	-0.08	-0.06	-0.11
5	0.31*	0.06	-0.14	0.08
6	0.25*	0.14	0.04	0.12
7	0.19	0.15	0.03	0.18
8	0.13	0.00	-0.01	0.01
9	0.20*	0.02	0.04	0.01
10	0.16	0.01	0.03	-0.02
11	0.17	-0.05	0.11	0.00
12	0.04	-0.02	0.09	0.12

Where star denotes statistical significance at the 95% significance level.

From the above autocorrelation function of returns we can notice that the first lag was significant in all cases and in some cases more distant lags alsoproved significant. Note that the highest first order autocorrelation appeared for the Banking sector, four times the standard error, and for the Food industry, more than five times the standard error.

Thus, I re-estimated the models by allowing past values of return to influence the current return. In these new models, as the appropriate in this case L.M. statistic indicated that there were no autocorrelation problem, giving supportive evidence that the omission of past returns from the initial models had led to model misspecification.

8.3.2 Risk as a Regressor

However, it is often argued that lagged variables which help to predict returns in a model like that proposed are merely *proxying for risk*. Thus, provided that we measure risk appropriately, there should be no link between the explanatory variables and the stock return, Engle Lilien and Robins (1987). For this reason I feel that I should include in the model a proxy for risk.

A traditional and simple way of proxying risk, is to use the squared value of the lagged returns, Merton (1980), Poterba and Summers (1986), French Schwert and Stambaugh (1987). Thus, the proposed model after the inclusion of the past returns and the risk proxy becomes :

$$R=\gamma\hat{\sigma}_t^2+\alpha_1(L)R_{t-1}+\alpha_2(L)MS_{t-1}+\alpha_3(L)I_{t-1}+\alpha_4(L)CB_{t-1}+\alpha_5(L)G_{t-1}$$
$$+\alpha_6(L)U.S_{t-1}+u_t$$

Where $\hat{\sigma}_t^2$ the proxy for risk, $(L)R_{t-1}$ past returns as the lag polynomial denotes and the other variables in stationary transformations as previously defined. Again under the efficient market Hypothesis $\alpha_1=\alpha_2=....=\alpha_6=0$.

The above model when estimated for all the examined indices indicated that the lagged return is a significant variable in explaining the current return. Lagged inflation rates, as expected, and foreign exchange rates appeared to be significant in some cases.

Nevertheless, the estimated models, except in one case, that of the Banking sector, did not pass the diagnostic test for stability and correct functional form. Additionally, the R^2 as a measure of explanatory power was low in comparison to the Banking sector.

For the case of the Banking sector the lagged returns at lags one and seven, in addition to other lagged explanatory variables, appeared highly significant. The model for the Banking sector passed the prediction stability test and the test for misspecification and wrong functional form. The F statistic for the inclusion of the lagged explanatory variables was high and the L.M test indicated that there was no problem of autocorrelated disturbances. Finally, the appropriate tests indicated that there was no problem of multicollinearity.

Analytically for the Banking sector I obtaind the following estimated model:

Index : <u>BANKS</u>

VARIABLES	Estimates and t statistics	Other statistics
R_1	0.30	$R^2=0.51$ $\bar{R}^2=0.46$
	(3.03)	$F=9.62$ $\bar{F}=5.60$
R_7	0.48	L.M(12)=9.72
	(4.12)	ARCH(1)=9.64
$INFL_4$	1.76.	Prediction Stability F=1.66
	(3.39)	RESET F=0.01
$M3_5$	-0.07	Normality(2)=1.87
	(1.64)	
CB_1	0.79	
	(2.23)	
CB_3	0.65	
	(2.93)	
$GOLD_1$	-0.14	
	(3.71)	
U.S $\$_2$	-0.43	
	(2.93)	
$\hat{\sigma}^2_t$	-0.31	
	(0.58)	

Notes:

1. The equation includes a constant. 2 Absolute t statistics in parentheses. 3. t statistics use heteroscedastic consistent standard errors according to White (1980) 4. The $\bar{F}$ refers to variables other than the lagged returns.

From the results it is easy for someone to see that the Bank returns are highly forecastable. As a crude overall measure of forecastability the usual R^2 statistic may be used. Ceteris paribus, the higher the statistic is, the higher will be the opportunity for someone to make a profit based on a predictive model suggested strategy. From the results the R^2 for the case of the Banking sector is 0.51 implying that 51% of the variation in returns in the Banking sector can be explained from the lagged explanatory variables in the model. It seems that stock price movements for monthly data are highly forecastable in comparison to daily data. Note though that as Fama and French (1988) suggested, the degree of the predictability rises with the forecast version. Thus in this case the R^2 is considerably higher than in the case of daily data.

Someone could still argued that the above statistical relationship exists because the risk proxy I used in the regressions, lagged squared return, is a crude and inappropriate measure of risk, since it measures the total variability of the returns and not the ex ante uncertainty regarding returns and as a consequence leads to inconsistent estimates. In order to take into account the above argument, I will try to re-estimate the model by using another more sophisticated measure of risk as proposed by Engle.

Engle (1982), introduced the A.R.C.H. model (Autoregressive Conditional Heteroscedasticity) In this model the unconditional variance $E(u_t^2)$ is constant but the conditional variance $E(u_t^2|X_t)$ is not. Denoting the conditional variance by σ_t^2 the model suggested by Engle is

$$\sigma_t^2=\sigma^2+\gamma u_{t-1}^2 \text{ where } \gamma>0.$$

In its standard form the A.R.C.H. model expresses the conditional variance as a linear function of past square innovations; in markets where prices are Martingale, price changes are innovations and this corresponds precisely to the Mandelbrott (1963), observation "*Large changes tend to be followed by large changes of either sign and small changes tend to be followed by small changes*". An unusually high disturbance term in one period results in an increase in uncertainty for the next period, Akgiray (1989), Bollerslev et al (1992).

The above A.R.C.H. model when extended to allow the conditional variance to be a determinant of the mean is called A.R.C.H. in M (Autoregressive Conditional Heteroscedasticity in Mean specification) and it is applicable in Finance since by using A.R.C.H. in M models we allow the time changing conditional variance to directly affect the expected return on a security.

The general form of the A.R.C.H. in M model is :

$$Y_t = \underline{X}_t'\underline{b} + \gamma\, g(h_t) + u_t$$

$$\text{where } h(t)=\mathrm{var}(u_t)=\text{A.R.C.H. }(q)=\alpha_0 + \sum_{j=1}^{q} \alpha_j u_{t-j}^2$$

By including a function of the variance as an explanatory variable in a model where the dependent variable is the stock return Engle (1987) argues that this may resolve many empirical findings like case where variables which helped to predict returns when correlated with risk loose their significance when a function of the conditional variance is included as a regressor. Furthermore, the possible heteroscedasticity in the disturbances, which I encountered to some extent in the model of the Banking sector, may have biased the "t" statistics leading to false finding of significant variables. I should note here that the method applied in a model which includes an A.R.C.H. in M function as an independent variable leads to more efficient estimates as well.

After simplification an A.R.C.H.(2) scheme seemed to be the appropriate specification for the A.R.C.H in M function . The final results with the M.L.E. method are presented in the following table. It is easy to note, in comparison with the O.L.S estimation, that the estimates are largely unchanged, as it is the fact that they are statistically significant indicating strongly the validity of the lagged explanatory variables to forecast the stock returns.

M.L.E. estimates Index: BANKS

VARIABLES	Estimates and t statistics	Other statistics
R_1	0.32	Squared coefficient between observed and preticted:0.49
	(4.05)	
R_7	0.37	
	(5.46)	
$INFL_4$	1.05	
	(3.04)	
$M3_4$	-0.06	
	(1.47)	
CB_1	0.63	
	(3.75)	
CB_3	0.61	
	(3.12)	
US $\$_2$	-0.48	
	(5.31)	
$GOLD_1$	-0.10	
	(2.54)	
$\hat{\sigma}^2_t$	-0.006	
	(1.07)	
alpha	0.38	
	(2.23)	
alpha	0.41	
	(2.03)	

In order to form the proxy for risk I take the log of the A.R.C.H. function as Engle suggests.

The most striking result from the above estimated model, I think, is the validity of lagged returns as predictors of the current return. The first order serial correlation is a common characteristic of all the examined indices. Additionally, in all estimated models the lagged return proved to be a significant explanatory variable. Note that this pattern of first order positive serial correlation was also prominent in the case of individual stocks. I will discuss the first order autocorrelation in detail later since I believe it is the most interesting element of my results.

Another lagged variable which proved to be statistically significant in explaining the current return is the seventh lag. Apart from the first order positive autocorrelation, which is common in all cases, in some cases more distant autocorrelations appeared to be significant, for the case of the Banking sector the sixth and the seventh lags, in the Textile industry the seventh lag, in the Steel industry the fourth and the fifth lags, and in the Food industry the sixth and the seventh lags. Surely, someone can argue that these autocorrelations are due to chance, but on the other hand they may be economically justified.

The autocorrelation at lag seven is based on observations seven months apart which imply that there are twelve pairs of observations which contribute to the seventh lag significant autocorrelation, i.e December-May, November-April, October-March e.t.c. I have to admit that I find very difficult to interpret theoretically this kind of anomaly. Nevertheless, a possible suggestion is that there is a pair or some pairs of observations which contribute most for the observed seventh lag autocorrelation.

In that sense, of particular interest is the December-May pair. The Greek Banks usuallypublish their Balance Sheets which refer to year t-1 in May of the year t. Lets us assume that the publication of the Balance Sheets in May cause share prices to react to the information contained in the Balance Sheets not previously known to the market participants. If in December of year t (the end of the financial year t) investors speculate on the performance of Banks in year t and take into account in their expectations with a relatively high weight the Balance Sheets results published in May, this will possibly result the seventh lag autocorrelation. The pair December-May exhibited a high Spiermann Rank correlation coefficient of 0.66

Finally, note the "wrong" sign of the expected volatility as a measure for risk under two different ways of risk modeling. Also, in both cases the risk as a regressor was insignificant. This "paradox" has been observed as well by French, Schwert and Stambaugh *(1986)* and Attanasio & Wadhwani (1989).

For the case of the traditional proxy for risk Attanasio and Wadhwani (1989), argued that the traditional risk specification is the reason for the puzzling paradox of the negative relationship between the return and the expected volatility. The above authors show with Monte Carlo simulation that if the true volatility is represented by an ARCH process then a measure of volatility based on past squared returns is likely to lead to a downward bias when giving appearance to the negative correlation. Additionally, their Monte Carlo results suggest that the traditional measure underestimates the degree of persistence in volatility. However in our case even when we used the ARCH-M specification of volatility the results have not changed.

One possible explanation is that the market is inefficient with respect to risk. Someone can also assume that the market slowly incorporates rising volatility in higher expected volatility under adaptive expectations; then expected risk will only rise gradually and therefore observe a negative relationship between ex ante risk and return , Attanasio and Wadhwani (1989).

A trading rule for the Banking sector based on the forecasted returns of the above model of the form:

$$\text{if } \hat{R} > 0 \quad \text{Buy Shares}$$

$$\text{if } \hat{R} < 0 \quad \text{Hold Cash}$$

and when transaction costs were taken into account, outperformed the Buy and Hold strategy for the period under examination.

TABLE 3.13

Trading rule results

(in wealth units)

Month/Year	B & H	T/R
1/81	100	100
6/81	90	96
12/81	92	98
6/82	94	101
12/82	101	102
6/83	74	95

12/83	64	89
6/84	68	88
12/84	69	83
6/85	74	91
12/85	101	122
6/86	107	129
12/86	170	205
6/87	278	312
12/87	379	523
6/88	281	536
12/88	261	492

9. Summary

In this chapter at the first part I tried to investigate if there are any predictive interrelationships between the stock indices of the Athens Stock Exchange, as such relationships exist for individual stocks. Simple Granger causality tests gave evidence that such relationships may exist. Cointegration analysis indicated that the Insurance Index of the Athens Stock Exchange is Granger caused by the indices of Banks and Miscellaneous firms, where there is a feedback causality between the Banking and Textile indices. In an effort to explain the statistical results of cointegration analysis in this study I interpreted the Error Correction Term which according to the Cointegration theory hold the cointegrating series in an equilibrium relationship as the interrelationship between the indices which is not known to the market participants.

In the secont part of this chapter I tried to investigate how stock prices react to past publicly availble information other than the price histories. As explanatory vatiables I used Money Supply measures, the Inflation rate, the exchange rate, the gold price and for the case of the Babks the Centarl Bank Certificate rate. My investigation for predictive relationships took place in low and high frequencies. For the low frequencies cointegration analysis indicated that such relationships do not exist, in the high frequencies the Granger causality tests yielded the same results.

The above tests examined the market efficiency with respect to an information set wich included only one variable each time. Since individual lags of some variables proved to be significant I tried to examine the combined predictive power of these lags. By using O.L.S. I encountered autocorrelation problem which resulted from the omission of lagged depedent variables as explanatoty variables in the model specification. In all cases the autocorrelation function indicated significant first order positive autocorrelation and in some cases more distant autocorrelations proved to be significant. Returns were positively serially correlated as the price changes of individual stocks in chapter one. Nevertheless, the only satisfactory model in econometric terms I could obtain was for the Banking sector where several lagged explanatory variables proved to be significant. The predictive validity of the explanatoty variables did not change even when I adjusted for risk in two different ways, with squared lagged returns and with A.R.C.H. in M. function. A trading rule based on the predicted returns of the model outperformed the Buy and Hold Strategy indicating inefficiency.

Notes

1.

The Dickey-Fuller test for the index price levels yielded the following results:

	A.D.F. statistic	
Variables	Levels	First Differences
Banks	-1.35	-6.59
Insurance Firms	-1.79	-9.31
Textile Ind	-1.46	-7.08
Food Ind	-0.96	-7.60
Miscellaneous Firms	-0.34	-6.95
Steel Ind	1.62	-6.75
Building Ind	-1.68	-6.44
Chemicals	-1.70	-7.04

2.

For the other pairs I obtained the following results:

Cointegration Results

Variables	CRDW	D.F statistic
Banks, Miscellaneous	0.16	-2.62
Banks Food ind.	0.12	-0.94
Banks Chemicals	0.16	-1.46
Banks Building ind.	0.04	-1.62
Banks Steel ind.	0.17	-1.42
Insurance Textile ind.	0.31	-0.96
Insurance Food ind.	0.24	-2.32

Insurance Chemicals	0.08	-0.83
Insurance Building ind.	0.12	-1.22
Insurance Steel ind.	0.34	-1.02
Textile ind. Food ind.	0.08	-1.57
Textile ind Chemicals	0.08	-0.82
Textile ind. Building ind.	0.06	-1.72
Textile ind. Steel ind.	0.21	-1.42
Miscellaneous Food ind.	0.19	-0.95
Miscellaneous Chemicals	0.05	-0.37
Miscellaneous Building ind.	0.02	-0.55
Miscellaneous Steel ind.	0.22	-1.79
Food ind. Chemicals	0.07	-1.97
Food ind. Building ind.	0.05	-1.41
Food ind. Steel ind.	0.59	-2.62
Chemicals Building ind.	0.20	-1.91
Chemicals Steel ind.	0.30	-1.91
Building ind. Steel ind.	0.12	-2.03

3.

If someone assumes that:

$$E(IR_t/I_{t-i-1})=E(IR_t) \text{ for all } i$$

which implies that the inflation rate has a stationary mean. Then in a regression of the form:

$$R_{jt}= \beta_0 + \sum_{i=1}^{n} \beta_i \quad (IR_{t-i}-E(IR_{t-i}/I_{t-i-1}) + u_t$$

where R_{jt} the return of index j at time t IR_t the actual part of Inflation at time t and $E(IR_t/I_{t-1})$ the expected (forecasted) part of inflation under the information set I_{t-1} of time t-1. Then the mean values weighted by the coefficients can be absorbed into the constant term of the equation, and the model becomes:

$$R_{jt} = \beta_0 + \sum_{i=1}^{n} \beta_j \, IR_{t-i} + u_t \qquad (1)$$

Where R_{jt} is the return of index j at time t and IR_{t-i} is the inflation rate attime t, where i=1,2,3....n In the above model the Efficient Market Hypothesis requires that $\beta_0=0$ and $\beta_j=0$ for all j.

In the previous chapter the Augmented Dickey Fuller tests indicated that the returns in question are integrated of order zero, that is they are stationary. The Augmented Dickey Fuller test for the inflation rate yielded a statistic of -3.46 which supports the assumption of stationarity, and it is a supportive evidence for the assumption that inflation rate has a stationary mean which we may assume that represents the market expectation. As an supportive evidence for the above assumption, that the mean value of the inflation rate can be considered as the expected part of inflation, the autocorrelation function of the inflation rate did not imply any AR or MA scheme where in the opposite case although the mean may be stationary, the autoreggresiveness of the series would imply that better predictions of the $E(IR_t/I_{t-1})$ are possible than only the mean value of a sample of past observations.

4.

The Cochrane-Orcutt is an iterative procedure. In the C-O procedure we estimate the initial regression by OLS and get the estimated residuals $\hat{u}_t$, then we estimate ρ, the correlation coefficient of the residuals as $\hat{\rho}= \Sigma\hat{u}_t\hat{u}_{t-1}/\Sigma\hat{u}_t^2$. Once an estimate of ρ is obtained we construct transformed variables of the original, say Y_t^* as $Y_t^*=Y_t-\rho Y_{t-1}$, and we estimate a new regression on the transformed variable. The new standard errors, from which the t statistics are calculated refer to the initial regression and they are asymptotic. In my case in order to estimate ρ, I used the C-O method until it converged.

5.

I could try a cointegration analysis at this point. Nevertheless, there are no critical values for cointegration between six variables. Engle and Yoo present critical values for the A.D.F. test for a maximum of five variables. Thus, although some judgment can be made on the basis of the correlogram of the residuals of the cointegrating regression someone should be very suspect for the validity of the results.

NOISE TRADING IN THE ATHENS STOCK EXCHANGE

Chapter four

4. Noise Trading in the Athens Stock Exchange

Overview

Our results in the previous chapter (ch. 3) indicated that all the examined stock market returns, exhibit first order positive autocorrelation. like the price changes of individual stocks on a daily basis (ch. 2). This pattern has been observed as well by other researchers who tried to explain it mainly as a no trading result, Perry (1985), Atchinson and Simonds (1987), Berglund and Liljembom (1988).

For the non trading explanation, the reasoning is that if share prices tend to react similarly to certain types of news and if some share prices react almost immediately whereas others, because of absence of trading experience a reaction delay, and an autocorrelation pattern is caused .

The institutional settings are believed to cause first order serial correlation. For instance in a market where rounds of auction are established for all stocks, and the stocks are auctioned one by one in the same order every day, serial correlation may arise when there is a reaction in the market not discernible during trading for the first stocks on the list, but clearly apparent when the majority of the stocks have already been auctioned. When this happens, stocks at the beginning of the list may be effectively hindered from an appropriate price reaction during the same day. These stocks will react when the new round starts the following trading period, thus creating serial correlation in the market return.

Nevertheless, research focused on this explanation gives little evidence that non trading creates the above mentioned autocorrelation pattern. Lo and MacKinley (1988) for instance, find little evidence for non trading as an explanation of positive autocorrelation in weekly U.S equity returns since 1962. For my results the non trading explanation is not a likely one, since in the Athens Stock Exchange there is no such practice which may cause the observed autocorrelation pattern (see ch 2.) although the first order autocorrelation pattern appeared in all the examined indices (see ch. 3).

Excluding the above factor as reasonable explanation, the observed autocorrelation can be explained as a slow reaction of the market to news or as a noise trading effect. Of particular interest is the second explanation, thus we will try to approach the statistical pattern based on investor beliefs and sentiment.

4.1 Noise Trading and Pseudoinformation

If we assume that some investors are not fully rational and their demand for risky assets is affected by their beliefs that are not fully justified by fundamental news and if we also assume that arbitrage, defined as trading by fully rational investors not subject to such sentiment is limited, then these two assumptions imply that changes in investor sentiment are not fully countered by arbitrageurs and so may affect security prices. Even if we relax the assumption of limited arbitrage, under the considered model of noise trading, profitable arbitrage will make prices deviate from fundamental values. According to noise theory in Finance as defined by Black (1986), noise traders are not fully rational investors and respond to signals which they believe convey information about future returns but in fact these signals do not convey any information in a fully rational model. Noise traders see information where it does not really exists. Undoubtedly, some shifts in investor demand for securities may be rational and reflect information which indeed affect the fundamentals of a security e.g growth of dividends, taxes or risk factors. Some demand changes though may be non rational.

Noise traders may base their investment strategy on subjective information which can be called mirage information in the sense of unrealistic information or "pseudosignals", DeLong et al (1990), i.e., signals which are not justified by information but from other reasons like investors psychology and beliefs. Of course the demand shifts because of noise trading are observable if the opinions, beliefs and trading strategies based on pseudosignals are the same, or at least correlated among noise traders. If noise traders with different models trade, then their models may cancel out and the noise trading effect on prices will hardly be observable.

There are reasons to believe that noise traders models or opinions will be correlated; for instance experiments have resulted that judgment biases afflicting investors in processing information tend to be the same among experiment subjects. Subjects in psychological experiments tend to make the same mistake, they do not make random mistakes, Shleifer and Summers (1990). One question here is how noise traders' beliefs which affect security prices are established.

The Efficient Market Hypothesis assumes that information is costlessly available to all market participants, but in the real world information is not costless. The investor who can not afford the cost of gathering and processing information is very likely to develop trading strategies based on subjective and unjustified beliefs. Investors who can not afford the cost of information may treat the price change or return at times t-i as a valid information for the next price change or return and trade on that "information". Their information set is in fact a pseudoinformation set. Taken into account the above possibility and my results, noise traders overweight the most recent price change or return, that of time t-1. In this case a possible model on which noise traders may base their investment decisions can be the following:

$$R_t^* = \alpha R_{t-1} + u_t \quad \text{with } \alpha > 0 \qquad (1)$$

where the star denotes the expectation.

The above model, which is called bandwagon expectations model, Maddala (1989), implies that investors "see" trends in price changes and returns. A price change may be interpreted as a signal that another price change of the same direction it will follow. Taking their expectation as a buying or selling signal since, *Res tantum valet* *quantum vendi potest*, noise traders will drive the price up or down therefore fulfilling their expectation.

Our statistical results do not conteradict the above kind of noise trading model. In addition, experiments relevant to financial markets show that the experiment subjects tend to extrapolate past time series which can lead them to chase trends. Experiments have shown that over short horizons, forecasters expect a price trend to continue even thoughthey expect a long run reversion to fundamentals. In a study Case and Shiller (1989) have found that home buyers in cities where the prices have risen rapidly in the past anticipate much higher future price appreciation than home buyers in cities where prices have been stagnant or have fallen.

Similar experimental results presented by Frankel & Froot, (1988) and Audereassen & Kraus, (1988). Anderseassen and Kraus (1988), in their experiment show subjects authentic stock price patterns, tell them that the stock patterns are authentic, and ask them to trade at given prices. They observed that their subjects instead of extrapolating price levels to arrive at a forecast of future prices, extrapolated price changes. Frankel and Froot (1988), in an investigation on U.S. dollar exchange rate found that when U.S dollar price had increased for some time the typical forecaster expected the dollar to continue to appreciate for the next month.

Results when the regression takes the form of model (1) and assuming that the actual return takes the place of the expected variable indicate that the lagged return is significant in explaining the current return for the cases of the Banking, Building and Food sectors of the Athens Stock Exchange. For the case of the other sectors the lagged return was not significant, at least at 5% significance level, and the R^2 indicated that the lagged return explain a low fraction of the variation of the current return in comparison to the Banking and Food sectors.

The autoregressions yielded the following results:

Banks

$$R_t = \underset{(2.40)}{0.40}\, R_{t-1} + \hat{u}_t \qquad R^2=0.16$$

Insurance

$$R_t = \underset{(0.61)}{0.21}\, R_{t-1} + \hat{u}_t \qquad R^2=0.04$$

Textiles

$$R_t = \underset{(1.42)}{0.34}\, R_{t-1} + \hat{u}_t \qquad R^2=0.12$$

Chemicals

$$R_t = \underset{(1.22)}{0.26}\, R_{t-1} + \hat{u}_t \qquad R^2=0.07$$

Food Industry

$$R_t = \underset{(2.58)}{0.56} R_{t-1} + \hat{u}_t \qquad R^2=0.31$$

Miscellaneous firms

$$R_t = \underset{(1.43)}{0.28} R_{t-1} + \hat{u}_t \qquad R^2 = 0.07$$

Building Industry

$$R_t = \underset{(2.97)}{0.35} R_{t-1} + \hat{u}_t \qquad R^2 = 0.08$$

Steel Industry

$$R_t = \underset{(1.58)}{0.16} R_{t-1} + \hat{u}_t \qquad R^2 = 0.02$$

For the case of the general Industrial and Commercial sector as a whole I obtained the following results.

$$R_t = \underset{(1.50)}{0.40} R_{t-1} + \hat{u}_t \qquad R^2 = 0.16$$

Where in the above regressions in the parentheses are the t statistics in absolute values, corrected for heteroscedasticity according to White (1980), when necessary.

It can be argued here that when noise traders form such models and make mistakes in their forecasts, why do they not then learn from their mistakes. Several reasons can be offered as an explanation for the fact that noise traders do not learn from their mistakes. First, noise traders can be overconfident with their forecasts, Kahnemann and Tversky (1973). When noise traders believe that they have found a good, in terms of forecastability, model they will probably develop a resistance to change such a model. People may also experience cognitive dissonance, Akerlof and Dickens (1982), defined as the capacity to filter, massage, manipulate or otherwise to process information to make it accord to strongly held internalised beliefs.[1] Thus, when people believe that they have developed a good forecasting model, failure of that model can be interpreted as "bad luck" and be ignored while success of the model can be interpreted as skill; people may have selective memory.

Also, noise traders since they are overconfident may become aggressive and bear more risk i.e., resale price risk. If risk trading is rewarding, noise traders can earn high expected returns. Noise traders then may become even more arrogant attributing again their investment success to skill in developing good forecasting models rather than luck, and thus their resistance to changing their forecasting model will strengthen.

When noise traders earn high expected returns many other investors may imitate them because, *"nothing can be more disturbing than see the man next door getting rich"* as Kindelberger (1978) noted, The new entrants may ignore the fact that noise traders bore more risk and just got lucky. These new entrants now, when subject to the same judgment mistakes add to the correlation of noise traders opinion and to the total effect on prices which may last for long.

There are additional reasons why noise traders may not learn from their mistakes. One such reason is that every episode might look different to noise traders, and so their learning from past mistakes may be limited. Also, it may take a long time for noise traders to enter into the market after a trade, and thus their mistakes may be forgotten while their prediction model remains the same, DeLong et al (1990).

4.2 Noise Trading and Arbitrage

As I mentioned before the above explanation stands well in the absence of arbitrageurs. Arbs, as they are called in U.S.A., are defined as investors who form fully rational expectations about security returns. Arbitrageurs play a central role in Finance, they trade to ensure that if a security has a perfect substitute then the price of the security will be equal to the price of the substitute; when the substitute is perfect, arbitrage is riskless.

Although riskless arbitrage ensures that relative prices are in line it does not apply well in the cases of stocks and bonds as a whole. These classes of securities do not have perfect substitutes and therefore if for some reason they are mispriced there is no riskless hedge for the arbitrageur. For instance, for an arbitrageur who thinks that stocks are underpriced can not buy stocks and sell the substitute portfolio since such a portfolio does not exist. The arbitrageur can simply buy stocks in hopes of an above normal return, but this is not riskless. If the arbitrageur is risk averse his demand for underpriced stocks will be limited.

It is argued, Shleifer & Summers (1990), that two kinds of risk limit arbitrage when noise trading exists. The first is the fundamental risk. Suppose that stocks are selling above the expected value of future dividends and an arbitrageur is selling them short. The arbitrageur then bears the risk that the realisation of dividends, or the news about dividends, will be better than expected. In such a case the arbitrageur may loose from his trade. Selling overvalued stocks is risky because there is always a chance that the market will do very well. Fear of such a loss, limits the arbitrageurs original position and keeps his short selling from driving prices back to fundamentals.

The second source of risk that limits arbitrage comes from unpredictability of future resale price. Suppose again that stocks are overpriced and an arbitrageur sells them short. As long as the arbitrageur is thinking of liquidating his position in the future he must bear the risk that at that time stocks may be even more overpriced, i.e continuous rising P/E ratios. If future mispricing is more extreme then the arbitrageur suffers a loss in his position. Again, fear for such loss limits the size of the arbitrageur position, and so keeps him from driving prices down to fundamental values. This second source of arbitrage risk, the resale price risk depends on the assumption that the arbitrageurs have a finite time horizon. If the arbitrageurs time horizon is infinite the arbitrageurs can sell the stocks short and pay dividends on them, in all the future periods, recognizing that the present value of these is lower than the proceeds from the short sale.

It can be argued that arbitrageurs may indeed have short time horizons. First, arbitrageurs may have to borrow cash or securities to implement their trades and as a result may have to pay the lenders per period fees. These fees cumulate over the period that the position remains open and can add to large amounts for long term arbitrage. The structure of the transaction costs thus induces a strong bias toward short horizons. An additional and I think very important reason is that the performance of most money managers is evaluated every few months limiting also the arbitrage horizon.

To the above reasons for limited arbitrage we can add a third one. Arbitrage relies on the proposition that arbitrageurs forecast accurately the fundamental value of a stock and thus take advantage of any deviations from fundamental values. The ability to forecast the fundamental value is a very difficult task. Summers (1986) shows that a time series of a share price which deviates from fundamentals, in a highly persistent way, looks a lot like a random walk. So it becomes very difficult to identify a mispriced series from a non mispriced series which behaves as a random walk as well.

Nevertheless, if someone wants to relax the above assumptions for limited arbitrage it can be argued that in the case of noise trading of the form I assume, arbitrage can destabilise prices even more. Bagehot in "Lombard

Street" (1872) wrote : "*owners of savings rush into anything that promises speciously, and when they find that these specious investments can be disposed of at a high profit, they rush into them more and more. The first taste is for high interest* (fundamental return), *but that taste soon becomes secondary. There is a second appetite for large gains to be made by selling the principal which is to yield the interest. So long as such cases can be affected the mania continues*". Knowledge of the noise traders bandwagon expectations model by arbitrageurs, may make it possible for the latter to try and exploit noise traders' profitably. The profitable trading strategy by speculators causes prices to deviate further from fundamentals.

Thus, it is possible when rational speculators receive good news and trade on this news they know, since they are rational, that the initial price increase will stimulate buying by the noise traders in the next time period, since noise traders trade on the model $R^*_t=\alpha R_{t-1}$ $\alpha>0$. In anticipation of noise traders' purchases informed rational speculators can jump on the bandwagon and buy more today and so drive prices up today, more than that which would be explained by the fundamental news. Next time period noise traders buy in response to todays price increase and so keep prices above fundamentals even if speculators are selling out. In such a case, at time t part of the price change is rational, due to good fundamental news, and a part of it due to the rational speculators' anticipatory trades. At time t+1 the price change will be partly because of noise trading, partly due tothe rational speculators possible reaction and part due to possible fundamental news. When rational speculators jump on the bandwagon and fuel noise trading they can add to the destabilisation of prices and the positive autocorrelation in short horizons.

Kindlerberger (1978), in his book "Manias Panics and Crashes" after distinguishing the investment societies of Apollonian as stabilising, and Dionisian as destibilising, vulnerable to euphoria and panics, he comments on price movements by considering two groups, insiders and outsiders. Insiders, Kindelberger argues, destabilise prices *"up and up"* and take advantage of the outsiders. Insiders in my case can be considered as rational speculators who know the behaviour of the noise traders, (outsiders). The term speculation seems appropriate in this case, following Keynes *"If I may be allowed to appropriate the term speculation for the activity of forecasting the psychology of the market"*.

The behaviour of market participants provides an additional evidence that they react to noise, in the sense of pseudosignals, Beneish (1991). It is well known that many investors follow the suggestions of the so called "market experts". "Market experts" can be professionals (even big investment firms), in the sense that they make money from their forecasts or they can be simple investors who believe, and make the others believe, that they are good forecasters. Let us say that a "market expert" at time t expresses the view that the stock market price for stock X at time t+1 will rise. The believers then they will try to buy in order to benefit from the "expected" rise. When these people buying they bid up the price so that at time t+1 the price of stock X is indeed higher. The "market expert" or in this case "opinion maker" is happy and probably richer since his predictions were fulfilled and the investors belief about the "market expert" predictions becomes stronger.

The above story of market behaviour is very similar to the "stone soup story", where a traveller persuades the people of a village that he is a magician and that he can make a soup from stones. When the water with a stone in, starts to boiling in the caldron the magician says "The soup would be much more tastier if we had some potatoes in...." and when the villagers offered some potatoes he goes ".......a bit of carrots" and finally "....a bit of meat". At the end when the soup was ready (the prices have driven up) the villagers were persuaded that the man who made a soup from stone was a magician (a good forecaster). Of course the magician in the above story can have some from "his" soup and the market experts can get a hudsome profit if they know that the other investors will follow their suggestions. The above arguments indicate that the key to investment success is not only predicting the future fundamentals but also predicting and feeding the noise traders demand . In a market with the above type of noise traders, rational investors can profit if they base their trading strategy on the noise traders' behaviour. Arbitrageurs then will try to predict trends, volume and many other indicators of noise traders' activity, following the Lord Keynes example of beauty contest but in a limited way i.e they will try to find only what the noise traders believe. This research area is a potential source of profits only in a market where investor sentiment influence prices. Shleifer and Summers (1990), express the view that "*Just as entrepreneurs spend resources to build casinos to take advantage of gamblers, arbitrageurs build investment banks and brokerage firms to predict and feed noise trading demand.*".

Thus, under the described model of noise trading it will pay arbitrageurs to become noise traders as well. In other words it pays the rational to become irrational in an irrational market. Thus in this case even ifwe relax the assumption of limited arbitrage, and assume that arbitrage exists, then profitable arbitrage will destabilise prices even more from fundamentals.

Of course such a strategy from the rational investors bears the risk that noise traders may change their opinion (model), about the price formation. In this case the rational investor should resign from the irrationality game, jump off the bandwagon, before the noise traders.

4.3 Trading Volume

The problem with the above noise trading hypothesis is that the variable R_t^* is not directly observable. The first order autocorrelation is consistent with the noise trading scenario but in order to investigate if there is any further evidence for noise trading activity in the Athens Stock Exchange, I will try to test if there is any relationship between trading volume and returns, because such relationships have been explained with a market segmentation approach, Copeland (1976).

Price-Volume relationship is important for stock price analysis and there have been offered at least four reasons for that, Karpoff (1987). First, the Price-Volume relation provides an insight into the structure of the financial markets. The theoretical models developed predict a price-volume relation which depends on market characteristics i.e., the rate of information flow in the market, the size of the market and short sale constraints. Second, the Price-Volume relationship is useful for event studies because if price and volume are jointly determined, then incorporating the Price-Volume relationship will increase the power of the tests. In some tests price changes are interpreted as the market evaluation of new information, while the corresponding volume is considered as an indication of the extent to which investors disagree about the meaning of the information. *"An important distinction between the price and volume tests is that the former reflects changes in expectations of the market as a whole while the latter reflects changes in the expectations of individual investors"* Beaver (1968). Third, the price volume relation is critical for the debate over the empirical distribution of speculative prices. One explanation for the kyrtotic shape of some return distributions is that the data are sampled from a mixture of distributions that have different conditional variances. Price volume tests generally support the mixture of distributions hypothesis. Finally, the price volume relation have significant implications for research into the future markets because it is argued that price variability may affect the volume of trade in future contracts.

An early empirical examination of the volume price relationship was conducted by Granger and Morgerstern (1963). Using spectral analysis of weekly data from 1939 to 1961 they could discern no relation between movements in a Securities and Exchange Commission Composite Index and the aggregate level of volume on the New York stock exchange. The above authors argued that in the stock market the classical theory of demand and supply does not apply and the reason they offered was that participants in the market can not be neatly divided into the groups of buyers and sellers and so *"there is not likely to be a clear cut relationship between volume and price or price change"*.

In 1964, Godfrey, Granger and Morgerstern with a new data set did not find any relationship between prices or the absolute value of price differences and volume. Subsequent empirical evidence Ying (1966), indicated that small volume is accompanied by a fall in price and large volume by a price rise, and that a large increase in volume is accompanied by either a large rise or fall in price. The above empirical evidence indicated a positive correlation between ΔP and V and $|\Delta P|$ and V.

Further empirical research confirmed the absolute price change volume correlation but with no evidence for causality. The discovered relation was almost entirely contemporaneous, as most leading and lagged variables were statistically insignificant, contradicting the old Wall Street proverb "it takes volume to make prices move" Copeland (1976) proposed a theoretical model of market segmentation to explain the contemporaneous positive price change-volume relationship. For Copeland's model simulation tests indicated that a segmented market can explain the observed correlation between V and $|\Delta P|$.

Another familiar Wall Street adage is that "Volume is relatively heavy in Bull markets and light in Bear markets". Following Ying's results empirical studies have shown a positive correlation between volume and price change *per se* but again no lagged relationship has been found implying a contemporaneous relationship between price change per se and volume, Rogalski (1978), Harris and Garel (1986).

In the case of the A.S.E. and since I have shown that there is evidence for the existence of noise traders and the way they behave I will try to investigate statistically if there is any relationship between trading volume and returns which will support the noise traders' existence.

The variables which I use for the statistical analysis are the monthly trading volume (the number of shares traded) and the price levels of the Banking and Industrial indices. In the stock market the trading volume for each stock or for all stocks in a particular time interval is regarded as an index measuring the activity of the stock or the market.

4.3 Volume and Prices in the Athens Stock Exchange

The A.D.F. test for stationarity on the trading volume yielded the following results:

	A.D.F. test results	
Variable	Levels	First difference
Volume for Banks	-0.77	-4.18
Volume for Industrial firms	-1.52	-3.23

From the above results we can see that the trading volume variables are integrated of order one, rejecting the hypothesis of stationarity in the trading volume series. In order to check again the above finding I used the minimum variance criterion, Pokorny (1980). According to the minimum variance criterion the differenced series of volume indicated smaller variance than the level series. Additionally, a double differencing of the series increased the variance indicating that the series of volume are first difference stationary i.e., integrated of order one.

The non stationarity evidence implies that the volume series is a highly correlated series. This was confirmed by the correlograms of the volume series which yielded a highly significant Box-Ljung statistic of $Q_{(12)}=136.3$ for the Banking sector and $Q_{(12)}=362,7$ for the Industrial Commercial sector.

Granger and Morgerstern, argued that an autocorrelated volume series may be due to the fact that activity in a stock excites further activity, or that information causing increased trading is not instantaneously absorbed by the market, both cases indicating market inefficiency. Osborne (1962), gave the following explanation which is inconsistent with the Efficient Market Hypothesis " *If volume measures interest in or attention to a stock, then interest is proportional to the interest already there i.e, people like sheep tend to develop more interest because it is already there (and conversely)*".

In the first place in order to assess any possible relationship between volume and prices I used the Granger causality test. The Granger causality test yielded the following results:

TABLE 4.1

Granger Causality Results

Variables	F statistic		Causality
Banks ind.-Banks vol.	$F_1=0.83$	$F_2=2.02^*$	<———
Indus. ind.-Indus. vol.	$F_1=1.46$	$F_2=2.19^*$	<———

F_1 refers to the regression where the price change is the dependent variable and F_2 to the regression where the change in volume is the dependent variable, star denotes significance at 5% significance level.

From the above results I have statistical evidence that in both cases the causality runs from prices to volume. Since the examined indices are also integrated of order one, I can apply cointegration analysis as described before and obtain more robust econometric results i.e., to see if the examined series exhibit a long run relationship.

The cointegrating regressions take the form :

$$V_{it}=a+\beta I_{it}+z_t$$

where V_{it} is the trading volume of sector i at time t, and I_{it} the index of sector i at time t.

For cointegration to hold the residual term of the above cointegrating regression must be integrated of order zero. The C.R.D.W. and A.D.F. cointegration tests for the pairs Banking index-Trading Volume of the Banking sector and Commercial Industrial index-Trading Volume of Commercial Industrial sector were as follows:

TABLE 4.2

Cointegration Results

	Cointegration statistics	
Variables	CRDW	ADF statistic
Banking index-Banking volume	1.31	-4.56
Industrial index-Industrial volume	0.75	-2.34

The CRDW statistic in both cases lead us to reject the Hypothesis of no cointegration. Nevertheless, the Augmented Dickey Fuller test as a more robust test for cointegration lead us to reject the Hypothesis of no cointegration only for the Banking sector. In order to test again for cointegration and the causal relationships which the Granger causality test indicated I used the error correction formulation

For the case of the Banking sector I obtained the following results:

TABLE 4.3

Error Correction Results

for Prices ΔP and Volume ΔV

Banking Sector			Industrial Sector		
Depedend Variable: Volume ΔV			Depedend Variable:Volume ΔV		
Variables	Estim.	"t"	Variables	Estim.	"t"
ΔV_{t-8}	-0.17	1.81	ΔV	-0.20	1.35
ΔV_{t-9}	-0.21	2.13	ΔV	-0.22	1.21
ΔV_{t-10}	-0.10	1.10	ΔI	2440	1.76
ΔV_{t-11}	-0.13	1.50	E.C.T	-0.25	1.27
ΔI_{t-1}	1380	2.84			
E.C.T	-0.84	7.13			
$R^2=0.36$	$\bar{R}=0.32$		$R^2=0.13$	$R^2=0.09$	
$LM_{(12)}=8.28$	$ARCH_{(1)}=0.79$		$LM_{(23)}=14.88$	$ARCH_{(1)}=12.32$	

As we can see from the above models the Error Correction term is significant in the case of the Banking sector indicating a long run Granger causality from prices to volume. The same does not apply for the case of the Industrial Commercial sector.

It is very interesting for the Banking sector that the price changeat period t-1 is related significantly and positively with the change in volume for the period t i.e, the lagged price change *"excites trading activity"*. This can be attributed to the character of the stock market influenced by psychological factors. That is to say, after a period of rises in prices the trading volume also increases due to the developed optimism among investors that prices will continue to rise *i.e,* $\Delta P_t^*=\alpha\Delta P_{t-1}$. *The* reverse situation may develop when prices fall. The investors may think that $\Delta P_t^* = \alpha \Delta P_{t-1}$, but they may also believe that the bad conditions will disappear soon and that price will rise again. So, they neither sell their holdings nor buy more stocks before the market settles down with the result of a fall in the amount of trading. Peters (1991), refers to evidence that when losses are involved people are more likely to gamble, in the sense to bet on a reversal which according to the model $\Delta P_t = \alpha \Delta P_{t-1}$ is not suggested.

4.4 Why the Banking Sector

The results give evidence that noise trading takes place mostly in the Banking sector of the Greek stock exchange. It seems that noise traders prefer the Bank stocks than the Industrial and Commercial stocks. I think it would be interesting to examine if there are any reasons for the above noise traders preference.

According to the Athens Stock Exchange official reports the Banking sector represents something less than 11% of the total number of companies listed in the A.S.E. but represents more than 55% of the total transactions every year and this is because the Banks represent about 50% of the twenty five most active stocks in the Greek stock market for every year. Banks also represent about 50% of the thirty largest companies based on market capitalisation. Additionally, in the examined period, almost all of the Banks, about 95%, appeared to report profits where the same did not happen in the other sectors Finally, Banks represent the majority of the firms with the most spread stocks in the A.S.E.

From the above facts we can see that the Bank firms can be characterised as Blue Chips with high marketability and may be preferred byboth noise traders and arbitrageurs. Stock brokers recommendation to their customers to buy shares of big corporations for which there is a very active market make Bank stocks preferable. Also, speculators have a real need for high marketability because they want to sell or buy at a very short period of notice. In addition, the profitability of the Banking sector and the fact the Banks are linked with the notion of trust provide another reason why Bank stocks are preferred. Additionally, Banks in Greece are well known firms and thus, although is an extreme case, may offer some kind of "psychic" dividends to their stockholders, Camerer (1990), just because they are well known.

Finally the noise trading effect in the Banking sector stocks helps to sketch the noise traders characteristics. As mentioned before the Banks represent the majority of the firms with the most spreadstocks in the A.S.E. That means that the Banking sector stocks are distributed in a large number of individual investors. These small individual investors are the people who can not afford the cost of gathering and processing fundamental information, and thus trade on mirage information.

4.5 Summary

The common statistical result of our analysis is that some price changes and returns in the A.S.E. are positively serially correlated. When we excluded the non trading effect as a reasonable explanation we tried to explain the above finding as a noise trading result. We defined noise trading as trading on unjustified information. Noise traders in the Athens Stock Exchange, are likely to observe returns or past price changes and "see" trends where they do not exist. Concerning arbitrage there are reasons to believe that it may be limited but also in the case of the noise trading we assumed it may be better for arbitrageurs to jump on the bandwagon and add to the noise effect on prices.

The first order autocorrelation pattern was highly significant in the Banking Sector as compared with the other sectors of the Athens Stock Exchange. In a further effort to investigate the noise traders' existence in the A.S.E. we found that the trading volume series is a highly autocorrelated series giving evidence that psychological factors may affect investors decisions. Granger causality tests indicated that lagged price changes Granger cause changes in volume in the Banking and Industrial-Commercial sectors. Nevertheless, cointegration analysis indicated that the above Granger causality exists only for Banking sector.

Finally, there are offered possible reasons why the Banking sector may be preferred by the noise traders in Greece. In an effort to sketch the noise trader in the

Athens Stock Exchange, we can say that noise traders are small investors since the stocks of the Banking sector are the most stocks in the Athens Stock Exchange.

Notes

1.

Analytically, Akerlof and Dickens (1982), say: *"In practice most cognitive dissonance reaction stem from peoples' view of themselves as smart nice people. Information that conflicts with this image tends to be ignored, rejected or accommodated by changes in other beliefs. Among other applications, persons who have made decisions tend to discard information that would suggest such decisions are in error because the cognition that the decision might be in error is in conflict with the cognition that ego is a smart person."*

FINAL SUMMARY

The statistical evidence in this study did not support the Efficient Market Hypothesis for the case of the Athens Stock Exchange. In chapter two the statistical results indicated that daily price changes of several individual stocks are not random. Price changes were found to be highly and positively serially correlated. Spectral analysis gave further evidence for the statistical dependence of price changes in the Athens Stock Exchange at low frequencies. From the high frequency correlation of price changes and by using Box-Jenkins methodology we formed forecasting models. A trading rule based on these forecasting models performed better than the passive buy and hold strategy in an out of the estimation sample period.

At the next stage we tried to investigate if there were predictive interrelationships between the examined stocks. For this purpose we used Granger causality tests and cointegration analysis. Cointegration analysis indicated that it is possible to predict the price movements of one stock by using information which is contained in the "price histories" of another stock. The above cointegration results proved to be profitable since a trading rule based on these results out performed again the buy and hold strategy. Predictive interrelationships were also found in chapter three, this time between stock market indices and once more the cointegration results proved to be profitable in practice.

Since the above results indicate violation of the Weak Form of Market Efficiency we tried to test the Semistrong Form of Market Efficiency by using information other than "price histories". In the estimated models and for all the examined indices we encountered problems of autocorrelated error terms which were due to the omission of lagged returns from the model specification. Index returns were found to be highly and positively serially correlated on a monthly basis like price changes of individual stocks on a daily basis. Taking into account the statistical dependency of index returns we could obtain a satisfactory in econometric terms model only for the case of the Banking sector. Even when we adjusted for risk the explanatory power of the model remained unaffected.

The prominent and common finding of all statistical analysis in this study is that the price change and return at time t, day or month, is positively and significantly related to price change and return at time t-1. One argument for the autocorrelation pattern is that the Greek market may be slow in incorporating available information into stock prices. In this case what distinguishes the Greek market from an efficient market is the speed of adjustment to new information. Nevertheless, the story which may describe the price formation in the Athens Stock Exchange can be much more complicated. Instead of assuming that the market reacts to information but in a slow fashion, it can be argued that the autocorrelation pattern is due to the fact that the Greek investors are influenced by forces other than rational and "see" information where it does not really exists. Investors in Greece may believe that there are trends in price changes i.e., tomorrow will be like today according to the model $\Delta P_t = \alpha \Delta P_{t-1}$ and trade on that "information" which in fact is a pseudoinformation, noise or mirage information. This unjustified belief may be the source of the autocorrelation pattern. Such market behaviour which can not be reconciled with a fully rational model of economic behaviour, introduces the element of irrationality in the stock prices formation.

The irrational forces will induce market inefficiency only if they are strong enough, thus, only a large group of irrational investors will lead to market inefficiency. Also it is required that the irrational forces should be correlated among the large number of the people comprising the irrational group. If we relax one assumption of the Efficient Market Hypothesis, the assumption that information is costless and available to all market participants, since real markets are characterised by costly information and budget constraints then it is likely for market participants without access to fundamental information to develop investment models unjustified by the economic theory. Psychological experiments in economics results tend to support the existence of this irrational behaviour.

On the other hand one can not reject the existence of market participants with the efficient market characteristics i.e., investors who can be characterised as rational investors. The major objection at this point is that when prices deviate from fundamental values because of the irrational behaviour of the market participants then the rational investors, who care only about intrinsic values, will engage in arbitrage and restore the equilibrium. Nevertheless, the arbitrage objection relies on the assumption that arbitrage is riskless, but this may not be true because there is fundamental and resale price risk for arbitrage activities. When rational investors are concerned *"not with what the investment is really worth to a man who buys it for "keeps", but with what the market will value it at, under the influence of pure psychology, three months or a year later."* then this limits their arbitrage activities but also make possible that the arbitrageurs will jump on the bandwagon. Then the irrational component of stock prices will become stronger since it would be generated by more investors, the rational and the irrational groups.

An empirical analysis for possible predictive relationships between trading volume and prices in the Athens Stock Exchange, gave supportive evidence to the hypothesis that forces other than rational play an important role for the price formation in the Athens Stock Exchange. The trading volume series were found to be a highly autocorrelated one and a causal relationship was found to be from prices to volume for the Banking sector.

In general the empirical analysis in this study indicated that the above type of noise is prominent in the

Banking sector of the Athens Stock Exchange. The Banking sector is characterised as the sector with the most spread stocks in Greece. That means that a large number of small investors hold Bank stocks, these investors are ordinary people who invest part of their money in the stock market.

Assuming the above description of stock price formation in Greece, then what are the implications, if any, for welfare and policy ? It is argued that noise trading, since it involves psychological and irrational forces, makes returns on assets more risky, Shleifer and Summers (1990). DeLong et al (1989), argued that the noise trading impact on society can be negative e.g the increased risk can reduce physical investment; the allocation of resources in an economy may fail because of noise trading and someone can wonder if there is any remedy to the noise trading.

Keynes wrote: "*That the sins of the London stock exchange are less than those of Wall Street may be due, not so much to differences in national character, as to the fact that to the average Englishman Throgmorton Street is, compared to Wall Street for the average American, inaccessible and very expensive. The introduction of a substantial government transfer tax on all transactions might prove the most serviceable reform available, with a view to mitigating the predominance of speculation over enterprise in the United States*". Thus, according to Kaynes we may apply the standard price theory, that is if we increase the cost of something less will be consumed. Sinse noise traders are ordinary people with limited income an increase in the cost of the Stock Market investment may limit their noise activities and thus prices may stop be influenced by noise trading.

In the case of the Athens Stock Exchange as already mentioned there are no capital gain taxes and the transaction costs are very low. It can be argued, that the introduction of capital gain taxes and an increase in the transaction costs may help to avoid the negative welfare effects of noise trading and increase the revenues of the public sector in Greece.

Nevertheless, the above "barriers to entry" solution can not be characterised as a fair one. With such cost bariers the Greek Stock market may be influenced by a relatively small group of people, those who can afford the cost of the stock market investment. Thus the above solution may lead to an economic oligarchy in a democratic political system. Then what is left for policy? As Black (1986), noticed for noise traders " *there is so much noise around that they do not know* (the noise traders) *they are trading on noise. They thinkthat they are trading on information.*". Thus, here it can be argued that if the Stock Market authorities educate and inform investors about the functions of the stock market and induces them to distinguish between noise and information, short term capital gain and long term yield, then prices may stop influences by noise and the stock market will fulfill its function for optimum allocation of resources in the Greek economy. Nevertheless I am not sure if investors are willing to miss all the fun of the "expensive hobby of investment" because as Black (1986) also noticed people may trade on noise *"because they like to do it."*.

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