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Can Stock Returns Be Predicted?

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CONTENTS

Abstract	2
SECTION 1	3
1.1 Introduction.....	3
1.2 Literature Review.....	4
1.3 Data.....	14
1.4 Definitions.....	15
1.5 Methodology.....	16
1.6 Estimation Results.....	23
SECTION 2	25
2.1 Introduction.....	25
2.2 Data and Methodology.....	26
2.3 Estimation Results.....	31
2.3.1 Group: "INTRACOM".....	32
2.3.2 Group: "PAPAELLINAS".....	33
2.3.3 Group: "FOURLIS".....	34
2.3.4 Group: "BIOXALCO".....	35
2.3.5 Group: "KLONATEX".....	36
2.3.6 Group: "ALFA-ALFA".....	38
References	40
Appendix A	42
Appendix B	48

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Abstract

This paper deals with the forecast of stock returns examined from two different viewpoints: On the one hand we try to find if the returns of stocks traded in the Athens Stock Exchange, can be predicted by the fundamentals of the relative companies; on the other hand, we try to capture in a model any relationship among the returns of stocks belonging to the same group of companies. Thus, the study is divided in two different sections: Section 1 deals with the predictability of fundamentals, while section 2 deals with the patterns among the affiliates in the same group of companies.

SECTION 1

1.1 Introduction

Although there is an extensive research in USA and Japan relating to the cross-sectional behavior of stock returns towards such variables as firm size, earnings yield, cash flow yield and book to market ratio, there is no similar research for the Greek market. Moreover, the available evidence on Greek stocks' returns suffers from methodological problems and an extremely limited database. For example, to the best of our knowledge, there is no information on delisted companies.

The purpose of our study is to explore the cross-sectional predictability of equity returns in Greece using the following variables: **size** (market capitalization of equity), **book to market ratio** and **price to earnings ratio**.

The choice of predictor variables is motivated by the existing evidence for the US and Japan markets which, in turn, is influenced by the practice of fundamental security analysts.

Our results, when placed alongside the evidence accumulated from studies of American and Japanese data, may also be useful in evaluating empirical models of the determinants of stock returns.

For this purpose, we collected data from 111 stocks listed in the ASE trading since 1992 on a continuous basis.

The remainder of the study is structured as follows. In section 1.2 a general literature review is presented. In section 1.3 we describe our data. Section 1.4 includes some valuable definitions concerning our variables. In section 1.5 we present the methodology for testing the relationship between stock returns and fundamental variables, while the results from the variable analysis are exhibited in section 1.6.

1.2 Literature Review

The theory existing until 1973 implied that the capital markets were perfect and also that the difference between the expected return on an asset and the expected return on the portfolio was proportional to the difference between the risk of the asset and the risk of the portfolio.

Fama and MacBeth (1973) posited that within the market, risk-averse investors made portfolio decisions period by period according to a two-parameter model.

Using the equation

$$E(R_i) = E(R_0) + [E(R_M) - E(R_0)] b_i$$

they tested three implications:

- ✓ That the relationship of the expected return on a security and its risk in any efficient portfolio is linear
- ✓ That b_i is a complete measure of the risk of security i in the efficient portfolio m
- ✓ That in a market of risk-averse investors, higher risk should be associated with higher expected return.

In their method, there are two categories of implications:

- a. the conditions of expected returns are implied by the fact that in a two-parameter world, investors hold efficient portfolios and
- b. there are also conditions implied by the assumption of the two parameter model that the capital market is perfect (no transaction or information costs).

Their hypothesis (that the returns of common stocks of NYSE reflected risk-averse investors' efforts to hold efficient portfolios) cannot be rejected when referring to NYSE common stocks between January 1926 and June 1968. They also concluded

that, on average, there seemed to be a positive tradeoff between return and risk. Moreover, they did not reject the hypothesis that no measure of risk, with the exception of portfolio risk, systematically affects average returns. It is worth mentioning that the fair game properties imposed on the coefficients and residuals are also consistent with market efficiency.

Subsequent to them, one of the first to search for a certain relationship between fundamentals and stock returns was **S. Basu (1977)**. In his article he connected the concepts of P/E ratio and market efficiency. Generally, a market is said to be efficient when security prices fully reflect available information in a rapid and unbiased fashion and thus provide unbiased estimates of the underlying values. In order to examine his hypothesis of market efficiency, Basu used a database of over 1,400 industrial firms, which listed on the NYSE between September 1956 – August 1971 posing a set of criteria as:

1. the same fiscal year-end of the firms
2. continuous trading of the firms for the entire period and
3. the existence of the relevant investment return and financial statements.

Basu ranked –on an annual basis- the P/E ratios, and, using the data available, constructed five portfolios (sorted by P/E ratio) for which he computed the returns for every month examined.

The model he preferred to use was based on the Sharpe-Lintner version of the CAPM and the performance measures of the portfolios were estimated by the Ordinary Least Squares method using finally 168 months of return data.

The conclusion he ran into was that low P/E portfolios earned more than that implied by their levels of risk, while the high P/E portfolios earned less than that implied by their levels of risk. Also, the same result seemed to hold true even if earnings were calculated after tax payments.

The results in this paper were consistent with the view that P/E ratio information was not fully reflected in security prices in as rapid a manner as postulated by the semi-strong form of the efficient market hypothesis.

As Fama (1991) pointed out, any correlation observed between fundamental variables and returns could be consistent with market inefficiencies, or with the fundamental variables proxying for omitted risk factors.

Yet, Roll (1981) posing for the first time the matter of the firm size effect (i.e. the size of a firm affects its return of common stocks), maintained that since the shares of small firms were generally the most infrequently traded and the shares of the large firms the most frequently traded, the betas for small firms were downward biased while the betas for large firms were upward biased.

For the period 1931 to 1975, Banz (1981) estimated a model of the form

$$E(R_i) = a_0 + a_1 \beta_i + a_2 S_i$$

where S_i is a measure of the relative market capitalization (size) for firm i . He concluded that the statistical association between returns and size was negative and of a greater order of magnitude than that between returns and beta documented in the earlier studies of the CAPM.

Reinganum (1981) using daily data from NYSE and AMEX stocks over the period from 1963 to 1977, showed that portfolios of small firms have significantly higher average returns than portfolios of large firms do. He also supported and extended Basu's (1977) findings to 1979 concerning the effect of P/E ratio on the returns of

common stocks, i.e. he found that there was significant negative relation between them.

On the other hand, in response to Roll's conjecture that the size effect may be a statistical artifact of improperly measured risk due to the infrequent trading of small stocks, **Reinganum (1982)** examined the daily returns of ten portfolios grouped on the basis of firms' size. The number of the firms he used ranged from 1,457 in 1963 to over 2,500 in 1970, while the portfolios were updated annually in relation to the market values of the common stocks of firms.

The methods he used to estimate the betas were the

- Ordinary Least Squares

$$R_{it} = \alpha_i + \beta_i R_{Mt} + \varepsilon_{it}$$

- Aggregated Coefficients Method proposed by Dimson.

$$R_{it} = \alpha_i + \sum_{k=-n}^T \beta_i R_{M,t+k} + \varepsilon_{it}$$

The OLS estimates indicated that small firms were less risky than large firms. On the other hand, the estimates of aggregated coefficients method indicated that small firms were more risky than large ones. However, according to the second method, the difference in estimated betas between the small firm and the large firm portfolios, could not explain the huge difference in average returns.

Additionally, he found that non-trading might be a serious concern for small firms, since the failure to account for it could lead to large underestimation of beta risk, but not large enough to explain for the firm size effect.

Keim (1983) based on Roll (1981), Banz (1981) and Reinganum (1981) tried to find the anomalies related to size and common stock returns. He used a sample of NYSE

and AMEX firms for the period from 1963 to 1979, the number of which ranged from 1,500 firms in 1963 to 2,400 in 1979. He estimated the size of these firms by multiplying the number of shares of common stock outstanding at year-end by the year-end price of the firms' common shares, and then divided the firms in ten ranked-by-size portfolios. Trying to extend Reinganum's (1982) results, he used three methods to estimate the betas of the portfolios:

- ✓ OLS betas that showed no distinguishable relation between beta and firm size.
- ✓ Scholes-Williams (1977) betas (higher than the corresponding OLS estimated), which indicated no distinct ordering of the betas according to firm size.
- ✓ Dimson (1979) betas that indicated a near monotone declining relation between firm size and betas.

Keim also tried to explain for the different behavior of the common stock returns that were taking place in January. So, based on his own research in 1982, he presented evidence that the January effect in stock returns was more pronounced for portfolios of small firms than for portfolios of large firms. This led him to suspect month-to-month instability in the size effect and he confirmed his suspicion by regressing the excess return for each day for the size portfolio to dummy variables indicating the month of the year. Using the Weighted Least Squares Method, he found that average excess returns for smaller firms were disproportionately large in January relative to the remaining eleven months, while January abnormal returns for the larger firm portfolios were negative and lower than the mean excess returns in any other month.

Keim also examined the hypotheses of Brown, Kleidon and Marsh (1983) that reported instability of the size effect from year to year during the 1967-1979 period but identified two distinct sub-periods when the relation between size and abnormal return was relatively stable.

More generally, Keim concluded that nearly fifty percent of the average magnitude of the size anomaly over the period 1963-1979 was due to January abnormal returns.

Further, more than fifty percent of the January premium was attributable to large abnormal returns during the first week of trading in the year.

Sanjoy Basu (1983) in order to examine the relations between E/P ratio, firm size and common stock returns, divided the securities first into groups on the basis of their E/P ratio and secondly on the market value of their common stocks. The portfolios were formed consisting of securities with similar E/P ratios but belonging to different market value classes or consisting of securities with similar market value of equity but belonging to different E/P classes. In such a way, firm size and E/P effects could be examined separately.

The data he used were accounting-earnings-per-share on a 12-month moving basis from December 1962 to December 1978.

The first statistics coming from the formation of the portfolios indicated some negative association between the two variables. This led Basu to the formation of two additional sets of size and earnings' yield portfolios by randomizing to E/P and market value. The measures of risk chosen were the standard deviation and the systematic risk; the latter measured in the context of the two parameter Capital Asset Pricing Model:

$$r_{p,t} - r_{f,t} = \delta_p + \beta_p (r_{m,t} - r_{f,t})$$

where:

$r_{p,t}$ = the return on portfolio p in month t

$r_{f,t}$ = the return on 'risk-free' asset in month t

δ_p = the differential or abnormal return for portfolio p (estimated OLS intercept)

β_p = the systematic risk for portfolio p (OLS slope)

$r_{m,t}$ = the return on the 'market' portfolio in month t

The presence or absence of E/P and size effects was tested in the context of Hotelling's multivariate T^2 methodology by assessing whether the vector of δ_p is significantly different from zero.

The empirical analysis showed that the common stocks of small NYSE firms appeared to have earned on average higher monthly returns than the common stocks of large firms. Additionally, portfolios of firms with high E/P ratios seemed to have earned higher rates of return than their low E/P counterparts.

Then, in order to test the homogeneity between alternative market value classes, he constructed earnings' yields portfolios. The idea was to rank annually securities included in a given market value class on the basis of their E/P ratios, and the market model regression was specified in an excess return form in order to include lagged, contemporaneous and leading market return terms. The results suggested that firm size might have an indirect effect on the risk-adjusted returns of NYSE common stocks: More specifically, the strength of the earnings' yield effect seemed to vary inversely with firm size. In addition, the empirical findings indicated that the E/P anomaly couldn't be attributed to earnings information effect.

The conclusion Basu ran into was that the effects of earnings' yield and size on expected returns were substantially more complicated than that previously documented.

On the other hand, Jaffe J., Keim D. and Westerfield R. (1989) examined the effect of size and P/E ratio on stock returns but with a much bigger sample, and data free of survivor biases. They did both portfolio and seemingly unrelated regression tests and laid emphasis on the important differences between January and other months. More specifically, they collected data for the period between 1951 and 1986 while the number of firms chosen ranged from 352 in 1950 to 1.309 in 1974.

Firms were ranked on the ratio of year-end earnings to share price at the end of March in each year and placed into one of six groups (Group 5 had the highest E/P). Each

E/P group was then divided into five subgroups on the basis of size, so this procedure resulted in 30 subgroups or portfolios updated annually.

The same ranking also took place in the opposite way, that is, the firms were first ranked on market value and then on E/P.

One of their results was that returns were negatively related to market value and average returns tended to be positively related to the E/P ratio. At the same time, market values appeared lower when E/P was higher suggesting a relation between the two variables.

A second method they employed was the use of a SUR¹ (seemingly unrelated regression) model in order to simultaneously adjust for portfolio risk and test for the significance of the size and E/P effects. The SUR model was estimated using the monthly returns for 25 portfolios of positive-earnings firms for the period from April 1951 to December 1986, and also implied January anomalies expressed in dummy variables.

The writers also examined the influence of the price, since there was evidence of a relationship between the price and the market value given that the price is a component of P/E. There appeared to be a distinct relation between price, and E/P and size, i.e. the higher the E/P the lower the price and the smaller the size the lower the price. This suggested that the whole matter was substantially a price effect.

The negative relation between returns and size and/or price was primarily concentrated in January while the E/P effect was more pervasive throughout the remainder of the year. Their results did not suggest that price was a good surrogate for size since price seemed to have a separate influence on expected return.

¹ The SUR methodology gives asymptotically more efficient estimators than those using the OLS. It can be viewed as conducting a time-series regression for each of the 64 portfolios, requiring that the coefficients of the fundamental variables be the same across all portfolios and adjusting the estimates for the cross-correlation in the residual returns.

Besides, while in the USA there was voluminous research relating the cross-sectional behavior of stock returns to fundamentals of firms, Chan L., Hamao Y. and Lakonishok J. (1991) explored the cross sectional predictability of equity returns in Japan, using the variables: earnings yield, cash flow yield, size (market capitalization of equity) and book to market ratio.

For their study the writers used monthly data on stocks listed on the Tokyo Stock Exchange (TSE) from January 1971 to December 1988.

They also used two market indices: an equally-weighted and a value-weighted portfolio of all the stocks of the two sections (in Japan a distinction is being made to firms according to their size) of the TSE. As a risk free interest rate they used the call money rate and the 30-day Gensaki repo rate.

Trying to overcome the problems of the previous studies they also included delisted stocks and manufacturing companies. The analysis was conducted at the portfolio level, and three rankings were made for the portfolios. Firms were ranked on earnings yield as of the end of June in each year and placed into one of five groups. Each group was then divided into four subgroups by increasing size values and third, each group was divided into five groups based on book to market ratio.

As Jaffe J., Keim D. and Westerfield R (1989) did, they used the Seemingly Unrelated Regression (SUR) model to adjust for portfolio risk and test for the significance of the fundamental variables.

$$R_{pt} - R_{ft} = a_0 + b_{p1}(RW_t - R_{ft}) + b_{p2}(R_{et} - R_{ft}) + a_1(E/P)_{pt} + a_2(LS)_{pt} + a_3(B/M)_{pt} + a_4(C/P)_{pt} + e_{pt}$$

According to the writers the SUR methodology has two main advantages:

1. betas are estimated simultaneously with the impact of the fundamental variables and
2. the procedure adjusts for the cross-sectional correlation in the residual returns across portfolios.

They used the SUR approach in contrast with the Fama - Macbeth methodology that allowed the coefficients of the explanatory variables to vary across months, while the OLS was likely to be inefficient, since the residuals across portfolio groups were in general correlated.

From their study we notice that high E/P stocks outperform low E/P stocks, while small stocks achieve substantially higher returns than large stocks. On the other hand, firms with large positive book to market ratios earn a premium over firms with low positive B/M ratios.

In the Japanese market, of the 4 variables considered, the book to market ratio and cash flow yield had a reliably positive impact on expected returns at least for the period in question. The performance of the size variable turned out to be highly dependent on the specific model and time period, yet no evidence of a strong positive earnings yield effect was found.

1.3 Data

The sample in this study consists of all firms listed in the Athens Stock Exchange between January 1992 and December 1999. The sample was identified through a search of ASE publications, the database of “Finance” and relevant press publications.

The reason why we did not use year 2000 in our study is that Greek companies had not yet published their balance sheets concerning the year mentioned earlier.

Of all the firms listed in ASE, 111 were listed before 1992 and the rest 340 after 1992. Since we needed firms with continuous dealing, we used only the 111 ones listed before 1992. Actually, due to a serious lack of data for all of the firms, we ended up dealing with 104 of them.

The daily data, i.e. the price of common stocks of the firms, the P/E ratio, the B/M ratio and the firm capitalization, are derived from the Database of “Finance”.

1.4 Definitions

Price to Earnings ratio:

The P/E ratio measures how much investors are willing to pay per unit of payment of reported profits. It is defined as

$$P/E = \frac{\text{stock price}}{\text{earnings per share}}$$

P/E ratios are generally higher for firms with higher growth prospects, other things held constant, but are lower for riskier firms.

Market to book ratio:

Market to book ratio is the ratio of the stock price to book value per share. Book value per share is just stockholders' book equity earnings- the net amount that the firm has received from stockholders or reinvested in their benefit. Companies with relatively high rates of return on equity generally sell at higher multiples of book value than do those with low returns.

Size:

The number of shares of common stock outstanding at year-end multiplied by the year-end price of the firm's common shares.

1.5 Methodology

In order to examine the relationship between our data we follow the next steps:

Step 1: For every firm attribute evaluated, we estimate its price on the 31 of December of each year examined, thus creating a set of yearly data for all the firms.

Step 2: For each variable a column in a table is created. We fill the columns reporting the data of every firm with chronological order, then placing each firm the one below the other.

The methodology used in this study is “pooling”, a method that connects the concepts of time-series analysis and cross-sectional data. The idea of pooling was created because data often contain information on cross-sectional units observed over time. In our case, the idea of using annual data for all the firms listed in ASE, forced us to use pooling because, while the number of firms’ stocks traded continuously on ASE is rather large, the data available for these firms do not exist before 1992, thus producing a disproportional relationship between the number of observations and the number of firms examined.

The most important advantage of pooling is that it may give the observer a great number of degrees of freedom that allows him to overcome the objective difficulties and restrictions of the linear model.

We try to estimate a model connecting the four variables we collected, starting from the formula:

$$R_{it} = a_i + b_i X_{it} + c_i Y_{it} + d_i S_{it} + e_{it} \quad (1)$$

where:

R_{it} : return of the price of common stock of firm i in year t

X_{it} : P/E ratio of firm i in year t

Y_{it} : M/B ratio of firm i in year t

S_{it} : size (market capitalization of equity) of firm i in year t

The whole purpose of the study is to assess the values of the parameters of this model.

As we will see next, we tried to estimate the same model using the excess returns of the stocks, i.e. their return over the returns of the year rate of T-Bills in Greece:

$$R_{it} - R_{ft} = a_i + b_i X_{it} + c_i Y_{it} + d_i S_{it} + e_{it} \quad (2)$$

First, we attempted to estimate model (1) using a sample period from 1992 to 1999. As E-Views excludes by default an observation if any of the explanatory or dependent variables for that cross-section is unavailable, we preferred to choose the Balanced Sample option that instructs E-Views to perform listwise exclusion over all cross-sections. Also, if all of the observations for a cross-section unit were not available, that unit would temporarily be removed from the pool for purposes of estimation.

With E-Views the choices for our explanatory variables were two:

- ✓ **Common coefficients:** The variables entered here are assumed to have the same coefficient across all cross-section members of the pool. A single coefficient is included for each variable.
- ✓ On the other hand, the **cross-section specific coefficients** are used when the variables have different coefficients for each member of the pool. A different coefficient would be included for each cross-sectional unit meaning that large numbers of coefficients may be generated (the number of these coefficients equals the product of the number of pool identifiers and the number of variables in the list).

For reasons of simplicity, we used the first choice for our coefficients; the numbers generated from the second choice would not be such important, since our examining period is just 8 years for each firm- a really small number of observations for analysis.

When it comes to the choices we had for the intercept, we tried to specify it by the alternative ways placed beneath:

- ✓ **None** no intercepts; $a_{it}=0$
- ✓ **Common** identical intercept for all pool members; $a_{it}=a$
- ✓ **Fixed effects** different intercepts estimated for each pool member;
 $a_{it}=a_i, E(a_i, e_{it}) \neq 0$

The fixed-effects estimator allows a_{it} to differ across cross-section units by estimating different constants for each cross-section. The fixed effects are computed by subtracting the “within” mean from each variable and estimating OLS using the transformed data:

$$y_i - \bar{y}_i = b' (x_i - \bar{x}_i) + (\varepsilon_i - \bar{\varepsilon}_i)$$

where $\bar{y}_i = \sum_t y_{it} / N$,

$$\bar{x}_i = \sum_t x_{it} / N \text{ and}$$

$$\bar{\varepsilon}_i = \sum_t \varepsilon_{it} / N$$

The fixed effects themselves are not estimated directly, but computed from

$$\hat{a}_i = \sum_t (\bar{y}_i - \bar{x}_i b_{FE}) / N$$

- ✓ **Random effects** treats intercepts as random variables across pool members;

$$a_{it}=a_i + u_i, E(u_i, e_{it}) \neq 0$$

The random effects model assumes that the term a_{it} is the sum of a common constant a and a time-invariant cross-section

specific random variable u_i that is uncorrelated with the residual ε_{it} . The random effects model is estimated by the following steps:

- (1) The residuals ε_{FE} from the fixed effects model are used to estimate the variance of ε_{it} .
- (2) The between-group (cross-sectional mean) model is estimated and the following is computed:

$$\frac{\hat{\sigma}_B^2}{T} = \frac{\varepsilon'_{BE} \varepsilon_B}{N - K}$$

where $\varepsilon'_{BE} \varepsilon_B$ is the SSR from the between-group regression.

- (3) OLS is applied to the GLS transformed variables (X includes the constant term and the regressors x)

$$y'_{it} = y_{it} + \hat{\lambda} \bar{y}_i, \quad X'_{it} = X_{it} + \hat{\lambda} \bar{X}_i$$

In the tables of Appendix we can see estimates of the values of the random effects. These values are computed using the formula:

$$\hat{u}_i = \frac{\hat{\sigma}_u^2}{\hat{\sigma}_B^2} \sum_i (y_{it} - X_{it} b_{FE})$$

yielding the best linear unbiased predictor of u_i .

For all of these choices, using E-Views we had three options of estimating weighted versions of our specifications:

- **No weighting** all observations are given equal weight.

The unweighted statistics are derived using residuals from the original model based upon the parameters and the estimated random effect from step (3) above:

$$\hat{\varepsilon}_{it} = y_{it} - X_{it}b_{RE} - \hat{u}_i$$

- **Cross section weights** GLS using estimated cross-section residual variances.

Cross-section weighted regression is appropriate when the residuals are cross-section heteroskedastic and contemporaneously uncorrelated.

- **SUR** analogue to Seemingly Unrelated Regression—GLS using estimated cross-section residual covariance matrix

With cross section weights, we could estimate a feasible GLS specification assuming the presence of cross-section heteroskedasticity. On the other hand, the option of SUR, estimates a feasible GLS specification correcting for both cross-section heteroskedasticity and contemporaneous correlation. Unfortunately, the SUR estimation cannot compute estimates for a model when we have large numbers of cross-sections or a small number of time periods (the average number of periods used in estimation must be at least as large as the number of cross-section units), and additionally, even if we had a sufficient number of observations, the estimated residual correlation matrix should also be nonsingular. Because of these pitfalls of the SUR methodology we did not select it for any of our analyses.

In addition, we had the choice of iteration to convergence, which controls the feasible GLS procedures. Its actual role was to update the weights and coefficients continuously, until they converged. It also estimated covariances that were robust to general heteroskedasticity, when cross section heteroskedasticity was selected, i.e. variances within a cross-section are allowed to differ across time.

If we would like to enter into some more technical details of our analysis, we could say that the class of models that can be estimated using a pool object can be written as

$$Y_{it} = a_{it} + x_{it} b_i + \varepsilon_{it}$$

where y_{it} is the dependent variable, and x_{it} and b_i are k -vectors of non-constant regressors and parameters for $i = 1, 2, \dots, N$ cross-sectional units. Each cross-section unit is observed for dated periods $t = 1, 2, \dots, 8$.

We can view these data as a set of cross-section specific regressions so that we have N cross-sectional equations:

$$Y_i = a_i + x_i b_i + \varepsilon_i$$

with 8 observations, stacked on top of one another. For purposes of discussion we will refer to the stacked representation:

$$Y = a + X b + \varepsilon$$

where a , b and X incorporate any restrictions on the parameters between cross-sectional units.

The residual covariance matrix for this set of equations is given by:

$$\Omega = E(\varepsilon\varepsilon') = E \begin{pmatrix} \varepsilon_1\varepsilon'_1 & \varepsilon_1\varepsilon'_2 & \cdots & \varepsilon_1\varepsilon'_N \\ \varepsilon_2\varepsilon'_1 & \varepsilon_2\varepsilon'_2 & & \\ \vdots & & \ddots & \\ \varepsilon_N\varepsilon'_1 & \cdots & \cdots & \varepsilon_N\varepsilon'_N \end{pmatrix}$$

The basic specification treats the pool specification as a system of equations and estimates the model using system OLS. This specification is appropriate when the residuals are contemporaneously uncorrelated, and time-period and cross-section homoskedastic:

$$\Omega = \sigma^2 I_N \otimes I_T$$

Our next steps were to estimate the following model using a sample period from 1992 to 1999:

$$R_{it} = a_i + b_i X_{it-1} + c_i Y_{it-1} + d_i S_{it-1} + e_{it}$$

i.e. the effect that our variables have on next year's returns.

An estimation of model (2), using excess returns for the period from 1992-1999, is presented in Appendix A. We also estimated our equation dividing the sample in two in order to find any patterns from 1992-1995 and 1996-1999 using excess returns.

The results of our research are presented in Panels A-D in the Appendix. Regarding the use of simple returns and contemporaneous effect of fundamentals on corporate stock returns, we observe that, in the overall period from 1992 to 1999, there are statistically significant coefficients when using a common intercept for all companies and cross section weights, or heteroscedasticity when using an intercept effect and cross section weights as described above. Our results are consistent with the literature on USA and Asian stock markets which is that the relationship between P/E, size and returns, while our findings conclude on a negative size effect.

Concerning the use of excess returns and contemporaneous effect of fundamentals on corporate stock returns, the results are similar to those since the coefficients are statistically significant for the same case as above, when using a common intercept for all companies and cross section weights, or heteroscedasticity when using a fixed effect intercept and cross section weights. The size and return coefficients are again consistent with Kingma (1981), Dam (1984), Chan and Westfeld (1989) or Chan, Hameed and Lakonishok (1991) and all three to Book Value ratios are given a positive sign. Once more, relative to the size coefficient, there is consistency with the literature.

The sub-period results in Panel C in the Appendix, yield totally different conclusions from those of the overall period reported in Panel A. In both sub-periods the size coefficient is positive, but really significant both with industry and with real life. It seems that large companies in excess outperform small companies. This specific discrepancy may be due to the fact that the distribution of the fundamental variables changes over time, and treating the observations on the unadjusted variables, fails to adjust for such changes. Or, on the other hand, the sample may be too small to represent the actual relationship between size and common stock returns.

From all our results, the most interesting are those presented in Panel D in the Appendix. This panel examines the use of simple returns and the effect of

1.6 Estimation Results

The results of our research are presented in Panels A-D in the Appendix. Regarding the use of simple returns and contemporaneous effect of fundamentals on common stock returns, we observe that, in the overall period from 1992 to 1999, there are statistically significant coefficients when using a common intercept for all companies and cross section weights, or inversely when using an intercept with fixed effects and cross section weights as described above. Our results are not consistent with the literature for USA and Japan, since all authors result in negative relationship between P/E, size and returns, while our findings conclude only in negative size effect.

Concerning the use of excess returns and contemporaneous effect of fundamentals on common stock returns, the results are almost the same since the coefficients are statistically significant for the same cases: that is, when using a common intercept for all companies and cross section weights, or when using a fixed effect intercept and cross section weights. The signs of two coefficients are again inconsistent with Reinganum (1981), Basu (1983), Jaffe, Keim and Westerfield (1989) or Chan, Hamao and Lakonishok (1991) since P/E and Price to Book Value ratios are given a positive sign. Once more, referring to the size coefficient, there is consistency with the literature.

The sub-period results in Panel C in the Appendix, yield totally different conclusions from those for the overall period reported in Panel A. In both sub-periods the size coefficient is positive; this really contradicts both with authors and with real life. It seems that large companies in Greece outperform small companies. This specific discrepancy may be due to the fact that the distribution of the fundamental variables changes over time, and pooling the observations on the unadjusted variables, fails to account for such changes. Or, on the other hand, the sample may be too small to express the actual relationship between size and common stock returns.

From all our results, the most interesting are those presented in Panel D in the Appendix. This panel concerns the use of simple returns and the effect the

fundamentals have on returns of next year. In this case, we observe coefficients that are really close to the ones mentioned by the authors that dealt with similar research.

In each estimation, except for the one that includes no intercept, the signs of the coefficients perfectly match the estimations of other authors. Reinganum (1981), Basu (1983), Jaffe Keim and Westerfield (1989) and Chan Hamao and Lakonishok (1991), resulted in a positive relationship between E/P and common stock returns and a negative relationship between size and returns. The signs of the parameters indicate that in Greece one can predict the positive (negative) course of the Greek firms stocks by observing a decrease (increase) in P/E ratio or a decrease (increase) in size. Unfortunately, none of our models keeps pace with the ones giving M/BV a negative value as referred in the literature. But, as it is generally accepted (Chan, Hamao and Lakonishok (1991)), the market to book ratio has the most significant impact on expected returns – this is also observable in panel D, since it is almost always statistically significant. It is really intriguing that this variable has received little attention in the academic literature, in comparison to size and P/E ratio. The noise in reported earnings may help to explain why the market to book ratio has such a strong influence and also why there is such an inconsistency with the results found by different authors.

SECTION 2

2.1 Introduction

In this section we will try to find models for the returns of the stocks belonging in the same group of companies. The groups we will be dealing with are:

GROUPS	COMPANIES
INTRACOM	INTRACOM S.A. INRASOFT S.A. INTRALOT S.A.
PAPAELLINAS	NOTOS HOLDING S.A. SPORTSMAN S.A. ENDISI S.A.
FOURLIS	FOURLIS S.A. KOTSOVOLOS S.A. RADIO KORASIDI S.A.
BIOXALCO	BIOXALCO S.A. ELBAL S.A. ELLINIKA KALODIA S.A. SIDENOR S.A. XALCOR S.A.
KLONATEX	KLONATEX S.A. FANCO S.A. DOUDOS S.A. GIANNOUSIS S.A. KLOSTIRIA NAOUSSIS S.A.
ALFA-ALFA	ALFA- ALFA COMPANY ALTE S.A.

The structure of this section is as following: In section 2.2 we describe our data and methodology, while in section 2.3 we present our estimation results as well as our conclusions on this study.

2.2 Data and Methodology

For every company used in our study, we estimated the returns for the period from 1/1/1999 to 31/12/2000, or alternatively, for the period for which all the companies of each group were actually traded on the ASE.

For these companies we tried to estimate a model connecting them in a single equation. The formula we used is:

$$y_i^A = c + \sum_{i=1}^{10} a_i y_{t-i}^A + \sum_{j=1}^{10} b_j y_{t-j}^B + \sum_{k=1}^{10} \gamma_k y_{t-k}^C + \varepsilon_i$$

where:

y_i^L : the return of the common stock of company L at t

In a few words, we try to estimate the relationship among the returns of each company in relation to its returns for the last 10 trading days and, at the same time, to the returns of the other companies in the group for the last 10 trading days.

The method we preferred is rather simple since after the initial estimation, we excluded the variable with minimum t-statistic in order to re-estimate the formula. This procedure took place several times until we resulted in a model that could describe in the optimal way the returns of the company and could also help in forecasting future quotations. Of course, not all the procedures ended in a model. There were some cases where no pattern could be located among the companies of the same group, so no model could predict future prices.

After every estimation, out of all the statistics generated, we gave special attention to Akaike Info Criterion and Schwarz Info Criterion defined as follows:

$$\text{Akaike info criterion (AIC)} \quad -2\ell/n + 2k/n$$

$$\text{Schwarz info criterion (SIC)} \quad -2\ell/n + k \log n/n$$

where k is the number of estimated parameters, n is the number of observations, and ℓ is the value of the log likelihood function using the k estimated parameters. The various information criteria are all based on minus 2 times the average log likelihood function, adjusted by a penalty function.

It is worth mentioning that the best model is the one described by the smallest information criterion.

Furthermore, when we concluded in a certain relationship between our variables we tried to move on forecasting the time-series already examined. Actually, in order to be more specific, we divided our sample in three different dates and forecasted the quotations coming after. For every forecast we made, we present the comparative diagram indicating the fitted and the actual course of the variables.

Actually, we tried to forecast the stocks' quotations in two different ways: dynamically and statically. When we selected **dynamic forecasting**, a multi-step forecast of Y was performed, beginning at the start of the forecast sample. For a simple single lag specification with two variables x and z and a constant c :

- The initial observation in the forecast sample would use the actual value of lagged Y . Thus, if S is the first observation in the forecast sample, the first observation for Y will be

$$\hat{y}_s = \hat{c} + \hat{a} x_s + \hat{b} z_s + \hat{k} y_{s-1}$$

where y_{s-1} is the value of the lagged endogenous variable in the period prior to the start of the forecast sample.

- Forecasts for subsequent observations will use the previously forecasted values of Y :

$$\hat{y}_{s+n} = \hat{c} + \hat{a} x_{s+n} + \hat{b} z_{s+n} + \hat{k} y_{s+n-1}$$

If there are additional lags of Y in the estimating equation, the above algorithm is modified to account for the non-availability of lagged forecasted values in the additional period. For example, if there are three lags of Y in the equation:

- The first observation (observation S) uses the actual values for all three lags, y_{s-3} , y_{s-2} and y_{s-1} .
- The second observation (observation $S+1$) uses actual values for y_{s-2} and y_{s-1} and the forecasted value of the first lag \hat{y}_s .
- The third observation (observation $S+2$) will use the actual values for y_{s-1} , and forecasted values for the first and second lags, \hat{y}_s , and \hat{y}_{s+1} .
- All subsequent observations will use the forecasted values for all three lags.

The selection of the start of the forecast sample is very important for dynamic forecasting. The dynamic forecasts are true multi-step forecasts (from the start of the forecast sample), since they use the recursively computed forecast of the lagged value of the dependent variable. These forecasts may be interpreted as the forecasts for subsequent periods that would be computed using information available at the start of the forecast sample.

Dynamic forecasting requires that data for the exogenous variables be available for every observation in the forecast sample, and that values for any lagged dependent variables be observed at the start of the forecast sample

On the contrary, **static forecasting** performs a series of one-step ahead forecasts of the dependent variable:

- For each observation in the forecast sample, we have

$$\hat{y}_{s+n} = \hat{c} + \hat{a}x_{s+n} + \hat{b}z_{s+n} + \hat{k}y_{s+n-1}$$

using the actual value of the lagged endogenous variable.

Static forecasting requires that data for both the exogenous and any lagged endogenous variables be observed for every observation in the forecast sample.

It is obvious that both methods always yield identical results in the first period of a multi-period forecast. Thus, two forecast series, one dynamic and the other static, are identical for the first observation in the forecast sample. Moreover the two methods differ for subsequent periods if there are lagged dependent variables. We actually divided the sample three times and conducted forecasts from three different points in time. The diagrams coming from our dynamic and static forecasts are really interesting so they are exhibited in Appendix B.

Furthermore, for the period 1/11/1999 – 30/11/2000 we conducted forecasts for all our variables using our models and dividing the time periods in 5-days sub-periods. The same forecast was also conducted for a model using our variable as endogenous and a constant c as exogenous, i.e.

$$Y_t = c$$

In order to examine the sufficiency of our models we used the criterion of Root Mean Squared Error for both forecasts for every sub-period. The model should give us a smaller RMSE for the 5-days period if it has been more accurate than the random walk forecast.

$$\text{RMSE} = \sqrt{\frac{1}{h+1} \sum_{t=s}^{s+h} (\hat{y}_t - y_t)^2}$$

We noticed that for most of the periods, our model described better the variable we wanted to estimate, so we moved on to forecasts for every period.

Our purpose was to create a portfolio consisting of the stocks for which we had a positive forecast for their return. In order to be more certain for our results, we rejected every positive forecast for which the Root Mean Squared Error of our model was bigger than the random walk's.

So we ended in a portfolio, which we restructured every period, leaving it “empty” if there was no positive forecast. The structure of our portfolio every period is presented in Appendix B.

In this sub-section we will provide the results that stemmed from our research for each country, sorted by group of companies. Then we will display the return of our portfolio compared to 7 benchmarks: the ASE market index and 6 “stock” mutual funds:

1. Alpha Ανταπόδοση
2. Alpha Μεσογείο
3. Alpha Small Cap
4. Στόχος Χρηματοοικονομικών Επιχειρήσεων
5. Interamerican Διεθνές
6. Interamerican Small Cap

Πανεπιστήμιο Πειραιώς

2.3 Estimation Results

In this sub-section we will present the models that stemmed from our research for each company, sorted by group of companies. Then we will display the return of our portfolio compared to 7 benchmarks: the ASE market index and 6 “stock” mutual funds:

1. Alpha Αναπτυξιακό
2. Alpha Μετοχικό
3. Δήλος Small Cap
4. Δήλος Χρηματιστηριακών Εταιρειών
5. Interamerican Δυναμικό
6. Interamerican Small Cap

Πανεπιστήμιο Πειραιώς

2.3.1 Group: "INTRACOM"

The group of "Intracom" constitutes of three companies listed on ASE: **Inracom S.A.**, **Intrasoft S.A.** and **Intralot S.A.**

a. INRACOM S.A.

$$\text{Rintracom} = -0.000406 - 0.019720 \text{Rintralot}_{(t-8)} + 0.145886 \text{Rintrasoft}_{(t-1)}$$

b. INRASOFT S.A.

$$\begin{aligned} \text{Rintrasoft} = & -0.002403 + 0.3497999 \text{Rintrasoft}_{(t-1)} - 0.133065 \text{Rintracom}_{(t-2)} - \\ & 0.138379 \text{Rintracom}_{(t-8)} + 0.173675 \text{Rintracom}_{(t-9)} \end{aligned}$$

c. INRALOT S.A.

$$\begin{aligned} \text{Rintralot} = & -0.000854 + 0.337013 \text{Rintralot}_{(t-1)} - 0.123202 \text{Rintralot}_{(t-5)} - \\ & 0.171243 \text{Rintracom}_{(t-2)} - 0.244611 \text{Rintracom}_{(t-8)} - \\ & 0.203934 \text{Rintrasoft}_{(t-8)} \end{aligned}$$

2.3.2 Group: "PAPAELLINAS"

The group of "Papaellinas" constitutes of three companies listed on ASE: **Notos Holdings S.A.**, **Endish S.A.** and **Sportsman S.A.**.

a. NOTOS HOLDINGS S.A.

$$R_{\text{notos}_t} = -0.001992 + 0.123348 R_{\text{notos}_{(t-9)}} + 0.109310 R_{\text{sportsman}_{(t-1)}}$$

b. ENDISH S.A.

$$R_{\text{intrasoft}_t} = 0.000108 + 0.315330 R_{\text{notos}_{(t-8)}} + 0.183867 R_{\text{notos}_{(t-9)}} + \\ 0.231691 R_{\text{notos}_{(t-10)}} + 0.151810 R_{\text{sportsman}_{(t-1)}} - 0.317140 \\ R_{\text{sportsman}_{(t-8)}}$$

c. SPORTSMAN S.A.

No model was able to describe Sportsman share's behavior according to our criteria.

2.3.3 Group: "FOURLIS"

The group of "Fourlis" constitutes of three companies listed on ASE: **Fourlis S.A.**, **Kotsovolos S.A.** and **Radio Korasidh S.A.**

a. FOURLIS S.A.

$$R_{\text{fourlis}_t} = -0.006331 + 0.148655 R_{\text{radio}_{(t-9)}}$$

b. RADIO KORASIDH S.A.

$$R_{\text{radio}_t} = -0.007603 - 0.163572 R_{\text{radio}_{(t-3)}} + 0.201486 R_{\text{radio}_{(t-9)}}$$

c. KOTSOVOLOS S.A..

No model was able to describe KOTSOVOLOS S.A share's behavior according to our criteria.

2.3.4 Group: "BIOXALCO"

The group of "Bioxalco" constitutes of five companies listed on ASE: **Bioxalco S.A.**, **Elbal S.A.**, **Ellinika Kalodia S.A.**, **Sidenor S.A.** and **Xalcor S.A.**.

a. BIOXALCO S.A.

No model was able to describe BIOXALCO S.A share's behavior according to our criteria.

b. ELBAL S.A.

No model was able to describe ELBAL S.A share's behavior according to our criteria.

c. ELLINIKA KALODIA S.A..

$$Relka_t = 0.001272 + 0.205124 Relka_{(t-1)} - 0.103142 Relka_{(t-2)}$$

d. SIDENOR S.A..

$$Rsidenor_t = -0.001532 + 0.240031 Rbioxalco_{(t-1)}$$

e. XALCOR S.A..

No model was able to describe XALCOR S.A share's behavior according to our criteria.

2.3.5 Group: "KLONATEX"

The group of "Klonatex" constitutes of five companies listed on ASE: **Klonatex S.A., Fanco S.A., Doudos S.A., Giannousis S.A. and Klostiria Naoussis S.A..**

a. KLONATEX S.A.

$$\begin{aligned} Rklonatex_t = & 0.001191 + 0.299511 Rklonatex_{(t-1)} - 0.128444 Rklonatex_{(t-2)} + \\ & 0.104060 Rklonatex_{(t-3)} + 0.102173 Rdoudos_{(t-10)} + 0.107384 \\ & Rfanco_{(t-1)} - 0.131015 Rgiannousis_{(t-4)} + 0.107687 Rnaouk_{(t-4)} \end{aligned}$$

b. FANCO S.A.

$$\begin{aligned} Rfanco_t = & - 0.002807 + 0.334055 Rfanco_{(t-1)} - 0.184004 Rfanco_{(t-3)} - \\ & 0.150434 Rdoudos_{(t-5)} + 0.192585 Rdoudos_{(t-6)} - 0.204891 \\ & Rgiannousis_{(t-6)} + 0.219501 Rnaouk_{(t-3)} + 0.118479 Rnaouk_{(t-9)} \end{aligned}$$

c. DOUDOS S.A..

$$\begin{aligned} Rdoudos_t = & 0.000812 + 0.304108 Rdoudos_{(t-1)} + 0.117669 Rfanco_{(t-9)} - \\ & 0.203705 Rgiannousis_{(t-4)} + 0.101781 Rklonatex_{(t-7)} + 0.148057 \\ & Rnaouk_{(t-4)} \end{aligned}$$

d. GIANNOUSIS S.A..

$$\begin{aligned} Rgiannousis_t = & 0.000772 + 0.264027 Rgiannousis_{(t-1)} - 0.164229 Rdoudos_{(t-4)} + \\ & 0.110070 Rfanco_{(t-1)} - 0.148376 Rfanco_{(t-3)} + 0.196529 \\ & Rklonatex_{(t-3)} + 0.120663 Rklonatex_{(t-4)} \end{aligned}$$

2.3.6 Group: "ALFA-ALFA"

e. KLOSTIRIA NAOUSSIS S.A.

$$\begin{aligned} \text{Rnaouk}_t = & 0.000721 + 0.348802 \text{ Rnaouk}_{(t-1)} + 0.101206 \text{ Rnaouk}_{(t-3)} - \\ & 0.127258 \text{ Rnaouk}_{(t-5)} - 0.159771 \text{ Rdoudos}_{(t-4)} + 0.120747 \text{ Rfanco}_{(t-5)} \\ & - 0.098519 \text{ Rklonatex}_{(t-2)} + 0.173724 \text{ klonatex}_{(t-4)} \end{aligned}$$

Πανεπιστήμιο Πειραιώς

2.3.6 Group: "ALFA-ALFA"

The group of "Alfa-Alfa" constitutes of two companies listed on ASE: **Alfa-Alfa Company S.A.** and **Alte S.A.**.

a. ALFA-ALFA S.A..

No model was able to describe ALFA-ALFA S.A share's behavior according to our criteria.

b. ALTE S.A..

No model was able to describe ALTE S.A share's behavior according to our criteria.

As it is easily noticeable, most of the returns of the firms' stocks could be described by a simple linear model, consisting of the returns of the firms' affiliates. All of the statistics produced by this procedure are exhibited in Appendix B.

These models were utilized for forecasting purposes: leaving a period of eleven months to be used as our information set, we conducted our dynamic forecasts, starting from 1/11/1999 for 5-days periods.

In case of predicting positive returns, the stock was eligible to appear in our portfolio, but only if it met our next criterion of RMSE – i.e. the forecast of the model should give a smaller RMSE than the random walk forecast – should it be included. This is how we selected the stocks to form our portfolio.

The portfolio was restructured every 5 days, while there were periods when it was zero. We also assumed no costs for every alleged transaction that took place in the beginning or at the end of the 5-days periods. We must also mention that each of the periods is not part of a whole week, but just 5 continuous days of trading.

Given our forecasts, we present the returns of our portfolio in a comparative diagram with the benchmarks we used.

Having 100 units of payment in the beginning of the period in question, we were able to gain 200 more units of payment, in contrast to the mutual funds, and the ASE market index. It is worth mentioning that only ALPHA METOXIKO mutual fund was in position to gain money in that period, while all the others fell below 100 units of payment.

Our results may seem really impressive compared to real returns for this period. It is rather obvious that our models describe the variables examined in the optimal way. Also, we had periods of stability, where no stock was chosen to appear in the portfolio as it is known that a zero return is better than a risky one for risk-averse investors.

We did not use any of the stocks for which we had big positive and smaller negative predictions for their returns in a certain period. One of our criteria was the existence of only positive predictions throughout the 5-days period.

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Appendix A

When	Authors	Data	Period in question	Methodology	Research	Result
1973	Fama E. Macbeth J.	NYSE common stocks	Jan 1926 – June 1968			Positive trade-off between return and risk
1977	Basu S.	NYSE common stocks	Sep 1956 – Aug 1971	Sharpe-Litner version of the CAPM - OLS	Market efficiency	Semi-strong form of market efficiency
1981	Banz		1931-1975	$E(R_i) = a_0 + a_1 \beta_i + a_2 S_i$	Size effect	Statistical association between returns and size is negative
1981	Roll					Infrequent trading of small firms, leads to downward biases of their betas
1981	Reinganum	NYSE and AMEX common stocks	1963-1977			<ul style="list-style-type: none"> • Small firms have higher returns than large firms • Negative relation between P/E and returns
1982	Reinganum		1963-1970	<ul style="list-style-type: none"> • OLS • Dimsons' aggregated coefficients 	Roll's Hypothesis	Non-trading cannot explain for the firm size effect
1983	Keim	NYSE and AMEX common stocks	1963-1979	<ul style="list-style-type: none"> • OLS • Dimsons' aggregated coefficients • Scholes-Williams betas 	Size anomalies and January effect	50% of size anomaly due to January abnormal returns
1983	Keim	NYSE and AMEX common stocks	1963-1979		Stability of the size effect from year to year	
1983	Basu	NYSE firms	1962-1978	CAPM	Relation between E/P, size and common stock returns	<ul style="list-style-type: none"> • Small stocks have higher returns • High E/P ratio stocks have higher returns
1989	Jaffe Keim Westerfield		1951-1986		<ul style="list-style-type: none"> • Effect of size and P/E ratio in common 	<ul style="list-style-type: none"> • Small stocks have higher returns • High E/P ratio

					stock returns	stocks have higher returns
1989	Jaffe Keim Westerfield		1951-1986		<ul style="list-style-type: none"> January effect 	<ul style="list-style-type: none"> Coefficients of E/P and size are significant in January but only E/P coefficients outside of January.
1991	Chan Hamao Lakonishok	TSE firms	1971-1988		Effect of earnings yield, cash flow yield, size and B/M ratio	<ul style="list-style-type: none"> High B/M ratio stocks have higher returns Small stocks have higher returns High cash flow yield stocks have higher returns

Panel A
Use of simple returns
Contemporaneous effect
Results

	c	coefficients of		
		P/E (se)	size (se)	P/BV (se)
Intercept				
		0,00009 (0,00011)	-0,12292 (0,10903)	0,01756 (0,030199)
Common				
No Weighting	4,28543 (2,533)			
Cross section weights	0,54625 (0,078285)	0,00036 (,000048)	-0,00633 (0,00333)	0,02498 (,003855)
Random effects				
No Weighting	4,99968 (2,2765)	-0,00007 (0,000109)	-0,15428 (0,09798)	0,02470 (0,02919)
No Weighting	NA	0,00013 (0,000073)	0,04505 (0,16347)	-0,00820 (0,0341)
Fixed effects				
Cross section weights	NA	0,00053 (0,00001)	-0,04954 (0,0074)	0,04609 (0,00513)
None				
No Weighting	NA	0,00009 (0,00004)	0,06096 (0,008374)	0,00507 (0,0249)
Cross section weights	NA	0,00036 (0,0165)	0,01649 (0,00038)	0,02405 (0,003484)

Panel B
Use of excess returns
Contemporaneous effect
Results

	c	coefficients of			
		P/E (se)	size (se)	P/BV (se)	
Intercept					
Common	No Weighting	0,00009 (0,00004)	-0,12298 (0,0827)	0,01761 (0,26415)	
	Cross section weights	0,00036 (0,00005)	-0,00996 (0,00374)	0,02646 (0,00434)	
Random effects	No Weighting	0,00007 (0,0001)	-0,15475 (0,098)	0,02486 (0,0293)	
	No Weighting	NA NA	0,04489 (0,16413)	-0,00812 (0,03421)	
Fixed effects	Cross section weights	0,00053 (0,00001)	-0,04117 (0,0078)	0,04242 (0,00573)	
	No Weighting	NA NA	0,00009 (0,00004)	0,00553 (0,025)	
None	Cross section weights	0,00036 (0,00005)	0,01085 (0,00042)	0,02526 (0,00397)	
	Cross section weights	NA NA			

Panel C
Use of excess returns
Contemporaneous effect
Results

	coefficients of						P/BV		
	c			P/E			Size		
	(se)			(se)			(se)		
	92-95	96-99	92-95	96-99	92-95	96-99	92-95	96-99	
Intercept									
Common									
	No Weighting	-0,18992 (0,6536)	8,73048 (3,8036)	0,00019 (0,00009)	0,00001 (0,000048)	0,01283 (0,02924)	-0,26898 (0,1591)	0,00452 (0,0055)	0,02670 (0,0503)
	Cross section weights	-0,35825 (0,01291)	-0,09000 (0,0499)	0,00021 (0,00002)	0,00034 (0,00003)	0,01045 (0,000582)	0,02077 (0,00229)	0,00217 (0,000471)	0,02775 (0,00067)
Random effects									
	No Weighting	-0,18289 (0,813)	10,25931 (4,35346)	0,00018 (0,000147)	0,00008 (0,00015)	0,01257 (0,035)	-0,33580 (0,1871)	0,00442 (0,0097)	0,03817 (0,05698)
	No Weighting	NA	NA	0,00031 (0,00007)	0,00022 (0,00013)	0,01923 (0,03926)	0,31037 (0,3398)	0,00572 (0,006327)	-0,04181 (0,09185)
Fixed effects									
	Cross section weights	NA	NA	0,00033 (0,000005)	0,00031 (0,000037)	0,05863 (0,000012)	0,32969 (0,0018)	0,00237 (0,0000028)	-0,04067 (0,00232)
	No Weighting	NA	NA	0,00019 (0,00009)	0,00011 (0,000047)	0,00468 (0,002587)	0,10516 (0,01627)	0,00515 (0,0059)	0,00539 (0,0502)
None									
	Cross section weights	NA	NA	0,00019 (0,000026)	0,00035 (0,000031)	-0,00440 (0,000078)	0,01687 (0,0002)	0,00375 (0,00052)	0,02827 (0,0006)
	Cross section weights	NA	NA						

Panel D
Use of simple returns
Effect on returns of next year
Results

	c	coefficients of			P/BV (se)
		(se)	P/E (se)	size (se)	
Intercept					
Common	No Weighting	3,28510 (1,8969)	-0,00011 (0,000095)	-0,09709 (0,081617)	0,04448 (0,021)
	Cross section weights	0,07489 (,466616)	-0,00012 (0,00003)	0,01300 (0,0198)	0,02033 (0,0047)
Random effects	No Weighting	3,62661 (1,61692)	-0,00010 (0,00009)	-0,11144 (0,06954)	0,04213 (0,0197)
	No Weighting	NA NA	-0,00012 (0,0001)	-0,05296 (0,121)	0,04596 (0,0251)
Fixed effects	Cross section weights	NA NA	-0,00013 (0,00003)	-0,02172 (0,03065)	0,02768 (0,0046)
	No Weighting	NA NA	-0,00011 (0,000096)	0,04382 (0,0064)	0,03602 -0,02041
None	Cross section weights	NA NA	-0,00012 (0,00003)	0,01613 (0,001622)	0,02026 (0,004613)
	Cross section weights				

Appendix B

Group 2.2.1:

INTRACOM S.A.

Dependent Variable: RCOM

Method: Least Squares

Date: 03/23/01 Time: 19:11

Sample: 11/01/1999 12/01/2000

Included observations: 285

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RLOT(-8)	-0.019720	0.006465	-3.050357	0.0025
RSOFT(-1)	0.145886	0.057405	2.541357	0.0116
C	-0.000406	0.001686	-0.240936	0.8098
R-squared	0.036246	Mean dependent var		-0.001137
Adjusted R-squared	0.029411	S.D. dependent var		0.029334
S.E. of regression	0.028899	Akaike info criterion		-4.239540
Sum squared resid	0.235515	Schwarz criterion		-4.201092
Log likelihood	607.1344	F-statistic		5.302843
Durbin-Watson stat	1.882763	Prob(F-statistic)		0.005486

INTRASOFT S.A.

Dependent Variable: RSOFT

Method: Least Squares

Date: 03/26/01 Time: 19:53

Sample: 10/21/1999 12/01/2000

Included observations: 292

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RSOFT(-1)	0.349799	0.061159	5.719457	0.0000
RCOM(-2)	-0.133065	0.081679	-1.629125	0.1044
RCOM(-8)	-0.138379	0.066397	-2.084113	0.0380
RCOM(-9)	0.173675	0.069788	2.488623	0.0134
C	-0.002403	0.001944	-1.236303	0.2174
R-squared	0.144169	Mean dependent var		-0.003423
Adjusted R-squared	0.132241	S.D. dependent var		0.036020
S.E. of regression	0.033554	Akaike info criterion		-3.934336
Sum squared resid	0.323128	Schwarz criterion		-3.871378
Log likelihood	579.4130	F-statistic		12.08663
Durbin-Watson stat	1.982292	Prob(F-statistic)		0.000000

INTRALOT S.A.

Dependent Variable: RLOT
 Method: Least Squares
 Date: 03/23/01 Time: 20:19
 Sample: 11/01/1999 12/01/2000
 Included observations: 285

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RLOT(-1)	0.337013	0.056060	6.011666	0.0000
RLOT(-5)	-0.123202	0.055626	-2.214829	0.0276
RCOM(-2)	-0.171243	0.076603	-2.235450	0.0262
RCOM(-8)	-0.244611	0.106790	-2.290581	0.0227
RSOFT(-8)	0.203934	0.087021	2.343511	0.0198
C	-0.000854	0.002230	-0.382792	0.7022
R-squared	0.160538	Mean dependent var		-0.001256
Adjusted R-squared	0.145494	S.D. dependent var		0.040509
S.E. of regression	0.037446	Akaike info criterion		-3.711008
Sum squared resid	0.391214	Schwarz criterion		-3.634114
Log likelihood	534.8186	F-statistic		10.67115
Durbin-Watson stat	1.953784	Prob(F-statistic)		0.000000

Group 2.2.2:

NOTOS HOLDINGS S.A.

Dependent Variable: RNOTOS

Method: Least Squares

Date: 03/24/01 Time: 16:43

Sample(adjusted): 1/25/1999 12/01/2000

Included observations: 485 after adjusting endpoints

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RNOTOS(-9)	0.123348	0.045047	2.738223	0.0064
RSMAN(-1)	0.109310	0.041978	2.603970	0.0095
C	-0.001992	0.002741	-0.727032	0.4676
R-squared	0.020808	Mean dependent var		-0.001924
Adjusted R-squared	0.016745	S.D. dependent var		0.060821
S.E. of regression	0.060310	Akaike info criterion		-2.772469
Sum squared resid	1.753181	Schwarz criterion		-2.746588
Log likelihood	675.3237	F-statistic		5.121379
Durbin-Watson stat	1.993459	Prob(F-statistic)		0.006297

ENDISH S.A.

Dependent Variable: REND

Method: Least Squares

Date: 03/27/01 Time: 09:46

Sample(adjusted): 1/26/1999 12/01/2000

Included observations: 484 after adjusting endpoints

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RNOTOS(-8)	0.315330	0.153436	2.055126	0.0404
RNOTOS(-9)	0.183867	0.064576	2.847303	0.0046
RNOTOS(-10)	0.231691	0.073524	3.151219	0.0017
RSMAN(-1)	0.151810	0.064504	2.353502	0.0190
RSMAN(-8)	-0.317140	0.144049	-2.201608	0.0282
C	0.000108	0.003082	0.035171	0.9720
R-squared	0.071831	Mean dependent var		-0.000248
Adjusted R-squared	0.062122	S.D. dependent var		0.073419
S.E. of regression	0.071102	Akaike info criterion		-2.437097
Sum squared resid	2.416494	Schwarz criterion		-2.385253
Log likelihood	595.7774	F-statistic		7.398464
Durbin-Watson stat	1.937309	Prob(F-statistic)		0.000001

Group 2.2.3:

FOURLIS S.A.

Dependent Variable: RFOURLI

Method: Least Squares

Date: 03/22/01 Time: 19:28

Sample(adjusted): 12/21/1999 12/01/2000

Included observations: 249 after adjusting endpoints

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RRADIO(-9)	0.148655	0.071685	2.073728	0.0391
C	-0.006331	0.004357	-1.452893	0.1475
R-squared	0.005845	Mean dependent var		-0.006765
Adjusted R-squared	0.001820	S.D. dependent var		0.070168
S.E. of regression	0.070104	Akaike info criterion		-2.469660
Sum squared resid	1.213916	Schwarz criterion		-2.441407
Log likelihood	309.4727	F-statistic		1.452123
Durbin-Watson stat	1.964863	Prob(F-statistic)		0.229341

RADIO KORASIDH S.A.

Dependent Variable: RRADIO

Method: Least Squares

Date: 03/23/01 Time: 18:22

Sample(adjusted): 12/21/1999 12/01/2000

Included observations: 249 after adjusting endpoints

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RRADIO(-3)	-0.163573	0.062056	-2.635880	0.0089
RRADIO(-9)	0.201486	0.074330	2.710702	0.0072
C	-0.007603	0.004464	-1.703218	0.0898
R-squared	0.016295	Mean dependent var		-0.007569
Adjusted R-squared	0.008297	S.D. dependent var		0.071711
S.E. of regression	0.071412	Akaike info criterion		-2.428716
Sum squared resid	1.254533	Schwarz criterion		-2.386337
Log likelihood	305.3751	F-statistic		2.037488
Durbin-Watson stat	1.940010	Prob(F-statistic)		0.132550

Group 2.2.4:**ELLINIKA KALODIA S.A.**

Dependent Variable: RELKA

Method: Least Squares

Date: 03/24/01 Time: 18:55

Sample(adjusted): 1/05/1999 11/28/2000

Included observations: 496 after adjusting endpoints

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RELKA(-1)	0.205124	0.050235	4.083306	0.0001
RELKA(-2)	-0.103142	0.050613	-2.037842	0.0421
C	0.001272	0.001569	0.810415	0.4181
R-squared	0.044922	Mean dependent var		0.001417
Adjusted R-squared	0.041047	S.D. dependent var		0.035572
S.E. of regression	0.034834	Akaike info criterion		-3.870388
Sum squared resid	0.598226	Schwarz criterion		-3.844945
Log likelihood	962.8563	F-statistic		11.59401
Durbin-Watson stat	1.993033	Prob(F-statistic)		0.000012

SIDENOR S.A.

Dependent Variable: RSID

Method: Least Squares

Date: 04/03/01 Time: 11:16

Sample: 1/14/1999 12/01/2000

Included observations: 492

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RBXAL(-1)	0.240031	0.054317	4.419041	0.0000
C	-0.001532	0.002487	-0.616001	0.5382
R-squared	0.018781	Mean dependent var		-0.001120
Adjusted R-squared	0.016778	S.D. dependent var		0.055315
S.E. of regression	0.054849	Akaike info criterion		-2.964404
Sum squared resid	1.474129	Schwarz criterion		-2.947337
Log likelihood	731.2434	F-statistic		9.378713
Durbin-Watson stat	1.295831	Prob(F-statistic)		0.002316

Group 2.2.5:

KLONATEX S.A.

Dependent Variable: RKLON

Method: Least Squares

Date: 04/01/01 Time: 18:18

Sample(adjusted): 1/15/1999 11/30/2000

Included observations: 490 after adjusting endpoints

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RKLON(-1)	0.299511	0.059677	5.018868	0.0000
RKLON(-2)	-0.128444	0.051687	-2.485017	0.0133
RKLON(-3)	0.104060	0.048120	2.162497	0.0311
RDOUD(-10)	0.102173	0.041509	2.461463	0.0142
RFANCO(-1)	0.107384	0.053111	2.021883	0.0437
RGIANN(-4)	-0.131015	0.051221	-2.557807	0.0108
RNAOUK(-4)	0.107687	0.055003	1.957831	0.0508
C	0.001191	0.002332	0.510839	0.6097
R-squared	0.159425	Mean dependent var		0.002118
Adjusted R-squared	0.147217	S.D. dependent var		0.055168
S.E. of regression	0.050945	Akaike info criterion		-3.099943
Sum squared resid	1.250987	Schwarz criterion		-3.031463
Log likelihood	767.4860	F-statistic		13.05953
Durbin-Watson stat	1.997938	Prob(F-statistic)		0.000000

FANCO S.A.

Dependent Variable: RFANCO
 Method: Least Squares
 Date: 06/18/01 Time: 17:47
 Sample: 12/31/1999 11/30/2000
 Included observations: 240
 White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RFANCO(-1)	0.334055	0.061877	5.398714	0.0000
RFANCO(-3)	-0.184004	0.075174	-2.447713	0.0151
RDOUD(-5)	-0.150434	0.063962	-2.351933	0.0195
RDOUD(-6)	0.192585	0.074129	2.597977	0.0100
RGIANN(-6)	-0.204891	0.076799	-2.667891	0.0082
RNAOUK(-3)	0.219501	0.082470	2.661578	0.0083
RNAOUK(-9)	0.118479	0.059497	1.991358	0.0476
C	-0.002807	0.003478	-0.807165	0.4204
R-squared	0.183981	Mean dependent var		-0.004540
Adjusted R-squared	0.159360	S.D. dependent var		0.059195
S.E. of regression	0.054274	Akaike info criterion		-2.956789
Sum squared resid	0.683387	Schwarz criterion		-2.840767
Log likelihood	362.8146	F-statistic		7.472461
Durbin-Watson stat	1.902385	Prob(F-statistic)		0.000000

DOUDOS S.A.

Dependent Variable: RDOUD

Method: Least Squares

Date: 03/27/01 Time: 10:48

Sample(adjusted): 1/14/1999 11/30/2000

Included observations: 491 after adjusting endpoints

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RDOUD(-1)	0.304108	0.048512	6.268660	0.0000
RFANCO(-9)	0.117669	0.042708	2.755230	0.0061
RGIANN(-4)	-0.203705	0.053785	-3.787358	0.0002
RKLON(-7)	0.101781	0.045129	2.255354	0.0246
RNAOUK(-4)	0.148057	0.055902	2.648499	0.0083
C	0.000812	0.002399	0.338472	0.7352
R-squared	0.153596	Mean dependent var		0.001800
Adjusted R-squared	0.144870	S.D. dependent var		0.056526
S.E. of regression	0.052272	Akaike info criterion		-3.052577
Sum squared resid	1.325183	Schwarz criterion		-3.001297
Log likelihood	755.4076	F-statistic		17.60250
Durbin-Watson stat	2.027576	Prob(F-statistic)		0.000000

GIANNOUSIS S.A.

Dependent Variable: RGIANN

Method: Least Squares

Date: 03/27/01 Time: 18:15

Sample(adjusted): 1/07/1999 11/30/2000

Included observations: 496 after adjusting endpoints

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RGIANN(-1)	0.264027	0.053671	4.919352	0.0000
RDOUD(-4)	-0.164229	0.055313	-2.969096	0.0031
RFANCO(-1)	0.110070	0.054053	2.036345	0.0423
RFANCO(-3)	-0.148376	0.053230	-2.787473	0.0055
RKLON(-3)	0.196529	0.053517	3.672264	0.0003
RKLON(-4)	0.120663	0.059182	2.038846	0.0420
C	0.000772	0.002376	0.324984	0.7453
R-squared	0.161371	Mean dependent var		0.001889
Adjusted R-squared	0.151081	S.D. dependent var		0.056384
S.E. of regression	0.051950	Akaike info criterion		-3.063044
Sum squared resid	1.319733	Schwarz criterion		-3.003677
Log likelihood	766.6348	F-statistic		15.68245
Durbin-Watson stat	1.972698	Prob(F-statistic)		0.000000

KLOSTIRIA NAOUSSIS S.A.

Dependent Variable: RNAOUK

Method: Least Squares

Date: 04/02/01 Time: 16:54

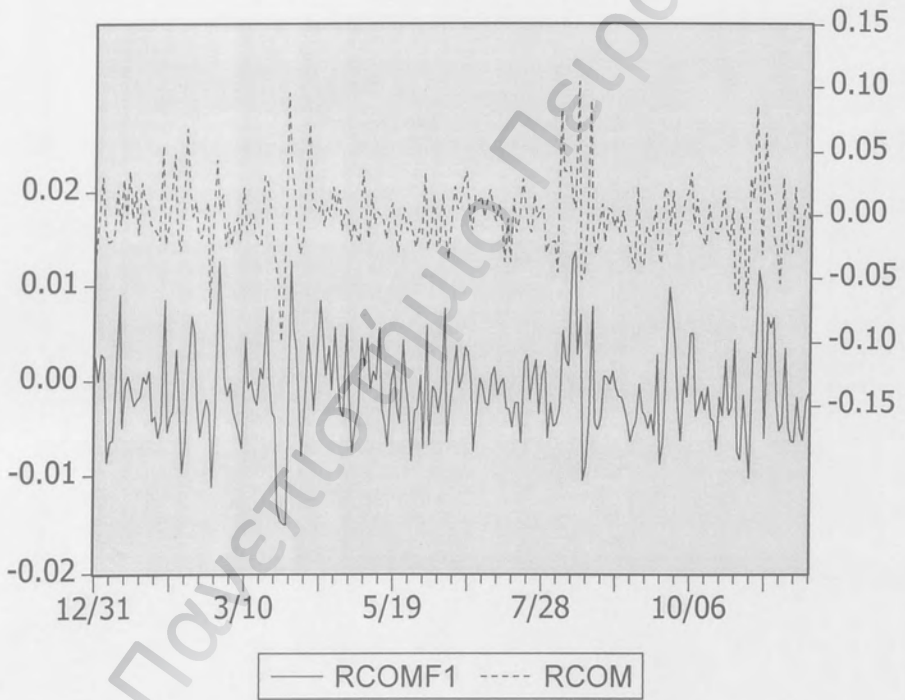
Sample(adjusted): 1/08/1999 11/30/2000

Included observations: 495 after adjusting endpoints

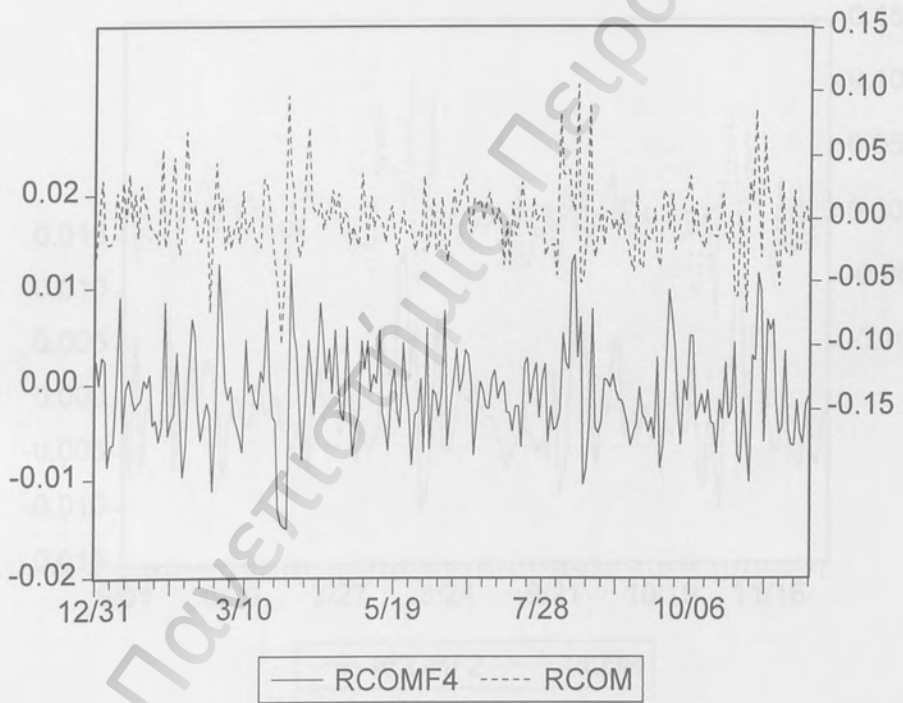
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RNAOUK(-1)	0.348802	0.048365	7.211804	0.0000
RNAOUK(-3)	0.101206	0.046852	2.160115	0.0313
RNAOUK(-5)	-0.127258	0.055343	-2.299458	0.0219
RDOUD(-4)	-0.159771	0.048419	-3.299737	0.0010
RFANCO(-5)	0.120747	0.053063	2.275535	0.0233
RKLON(-2)	-0.098519	0.048516	-2.030669	0.0428
RKLON(-4)	0.173724	0.057128	3.040974	0.0025
C	0.000721	0.002296	0.314061	0.7536
R-squared	0.156601	Mean dependent var		0.001335
Adjusted R-squared	0.144479	S.D. dependent var		0.054230
S.E. of regression	0.050160	Akaike info criterion		-3.131163
Sum squared resid	1.225310	Schwarz criterion		-3.063211
Log likelihood	782.9629	F-statistic		12.91795
Durbin-Watson stat	1.980550	Prob(F-statistic)		0.000000

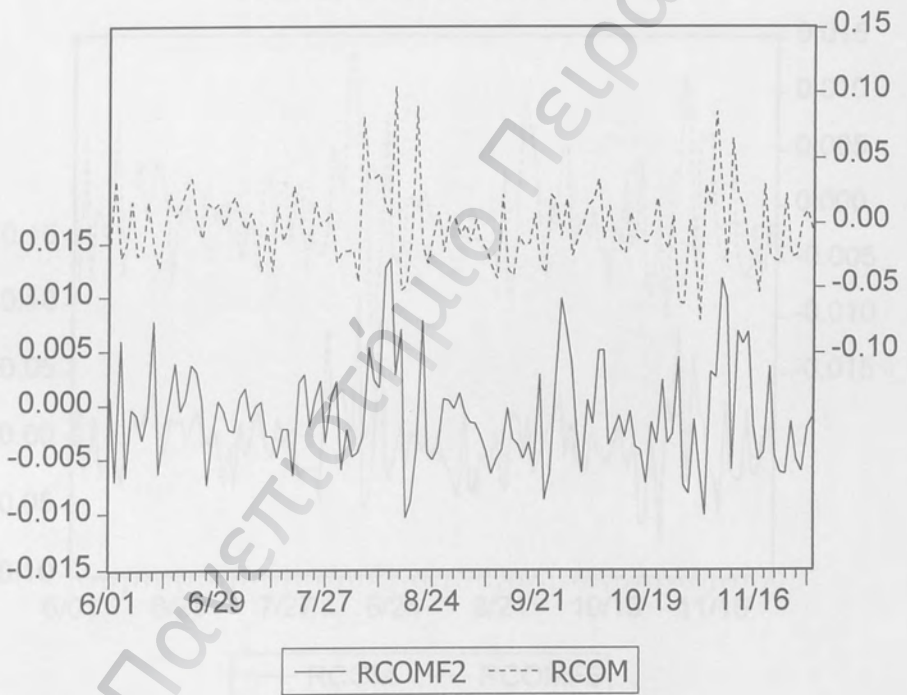
Intracom
Real and Forecasted series
Dynamic Forecast from 19/1/2000



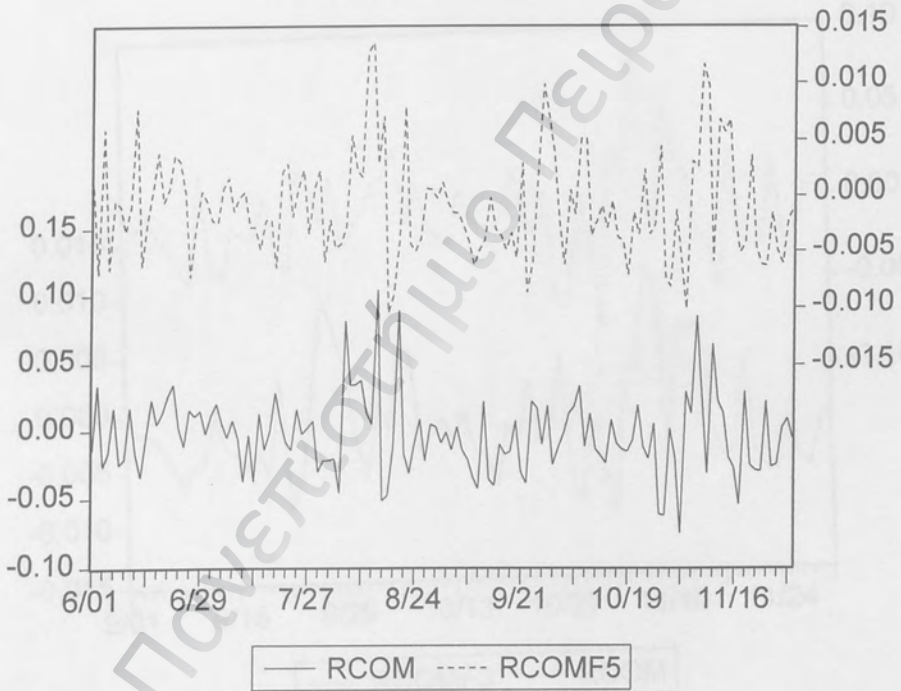
INTRACOM
Real and forecasted series
Static Forecast from 19/1/2000



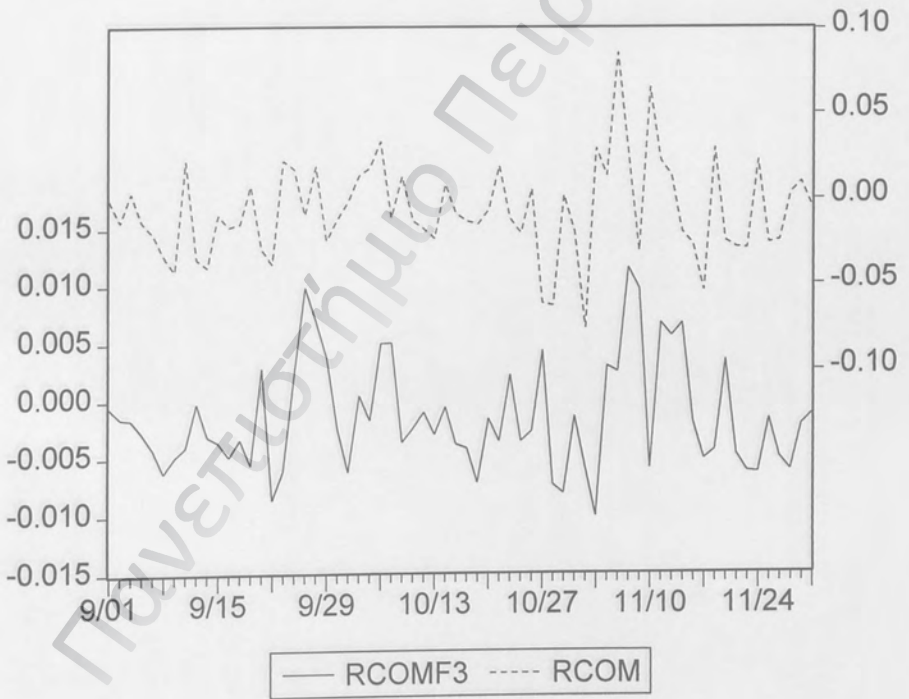
Intracom
Real and forecasted series
Dynamic forecast from 26/6/2000



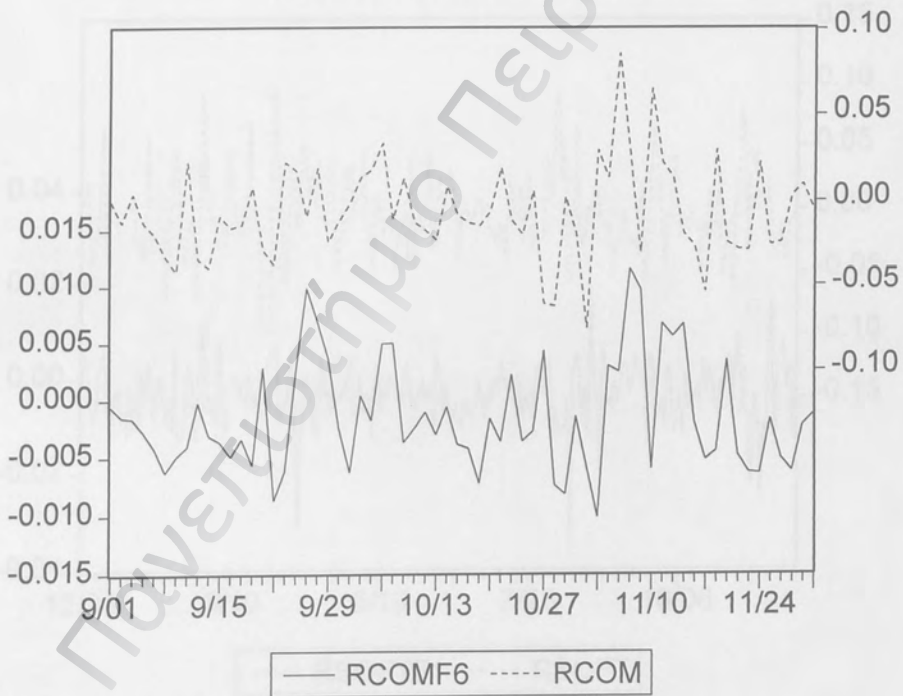
INTRACOM
Real and forecasted series
Static forecast from 26/6/2000



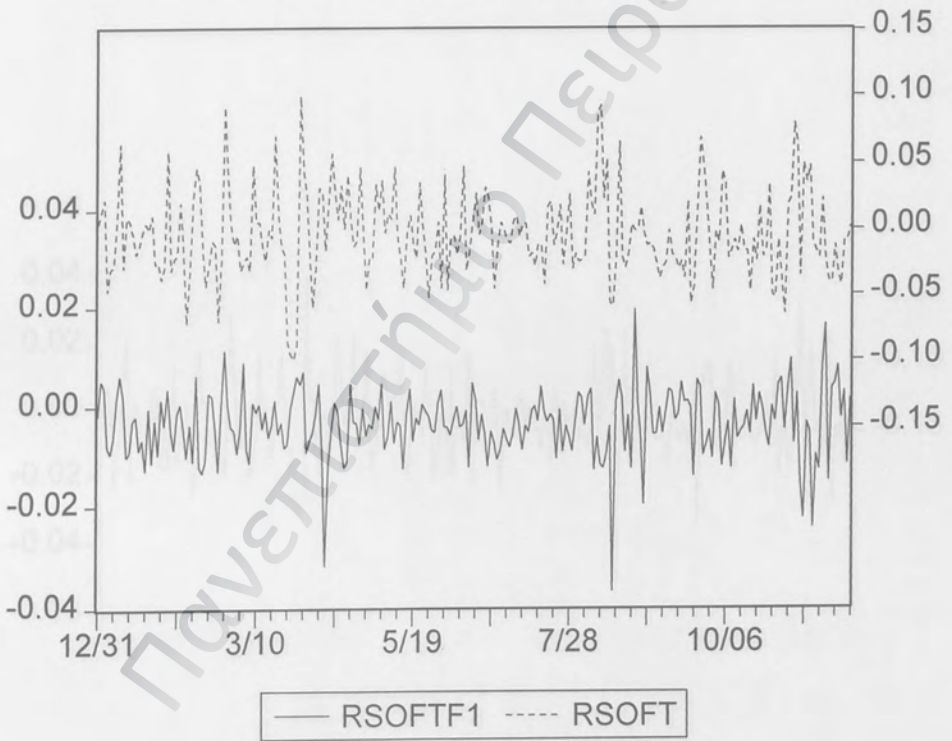
INTRACOM
Real and forecasted series
Dynamic forecast from 27/9/2000



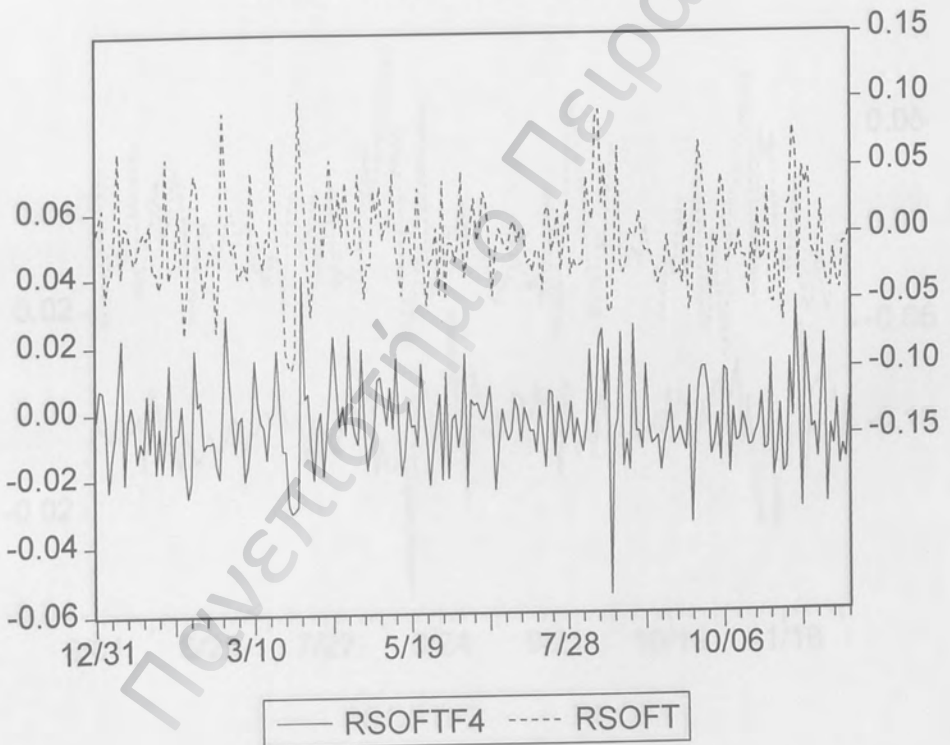
INTRACOM
Real and Forecasted series
Static forecast from 27/9/2000



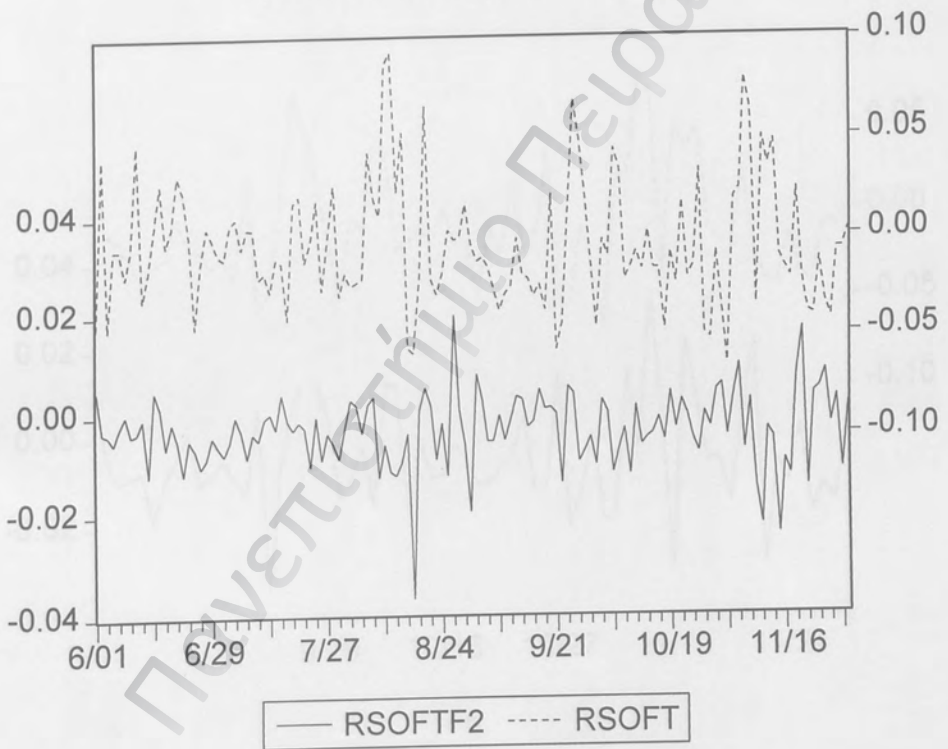
INTRASOFT
Real and forecasted series
Dynamic forecast from 19/1/2000



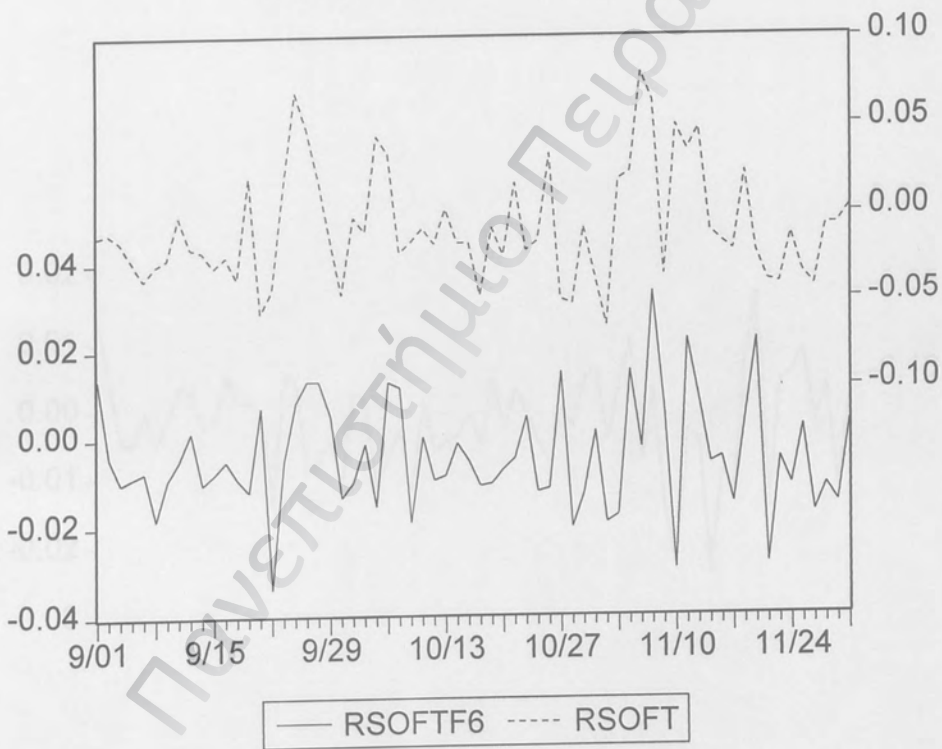
INTRASOFT
Real and forecasted series
Static forecast from 19/1/2000



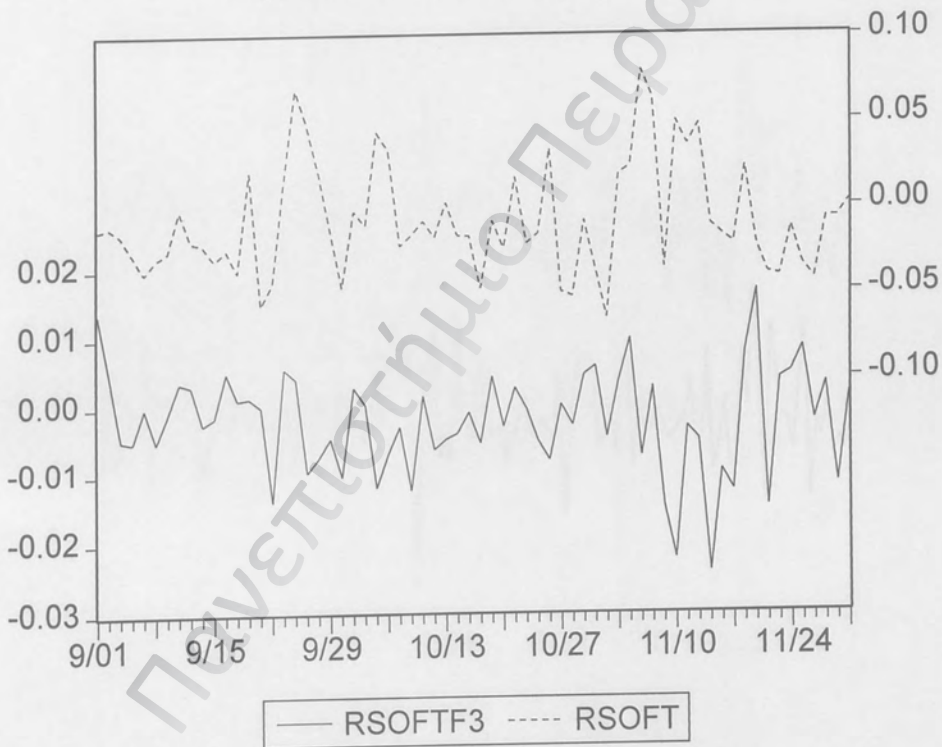
INTRASOFT
Real and Forecasted series
Dynamic forecast from 26/6/2000



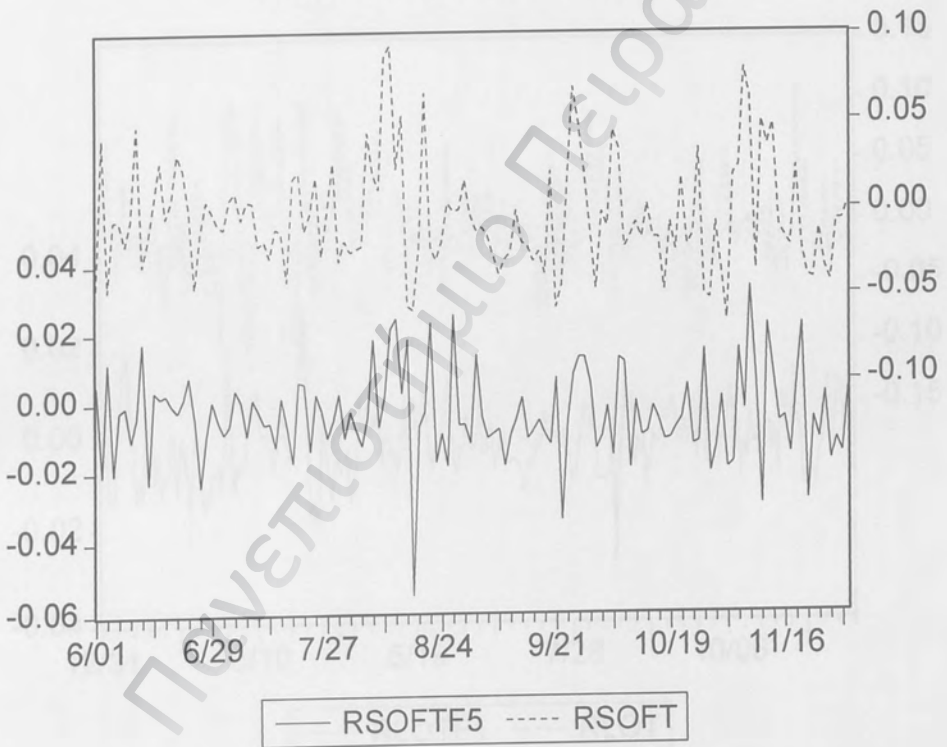
INTRASOFT
Real and forecasted series
Static forecast from 27/9/2000



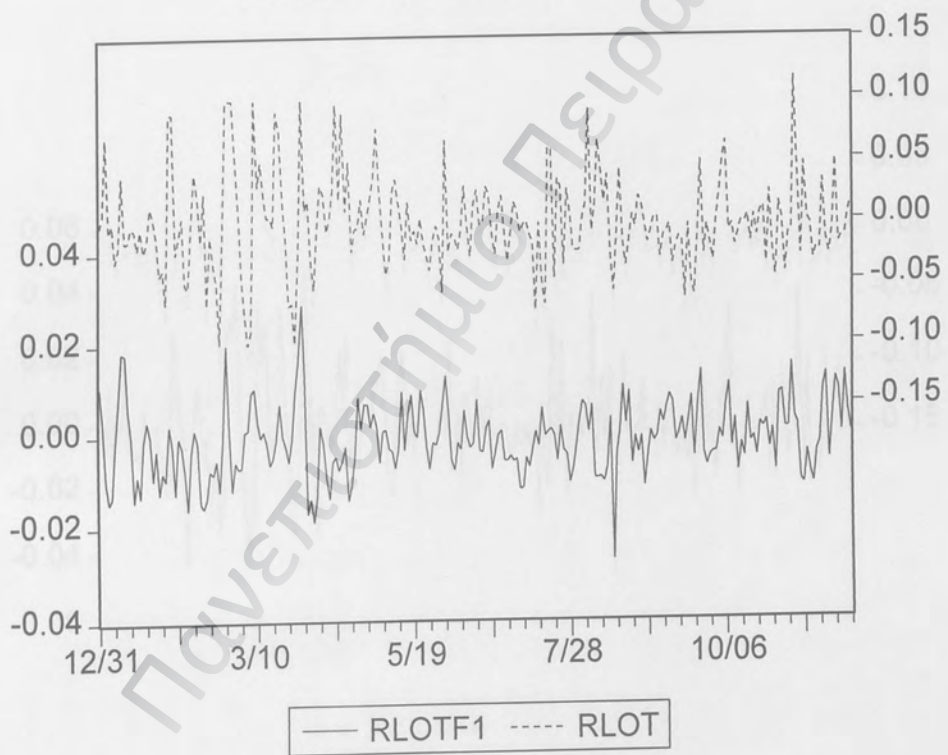
INTRASOFT
Real and forecasted series
Dynamic forecast from 27/9/2000



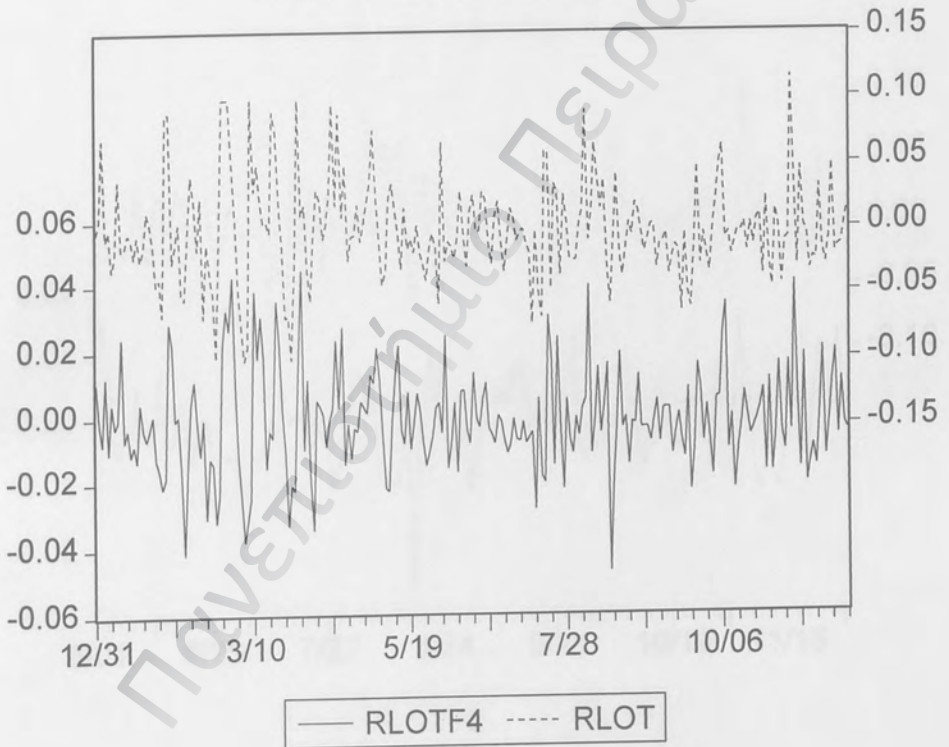
INTRASOFT
Real and forecasted series
Static forecast from 26/6/2000



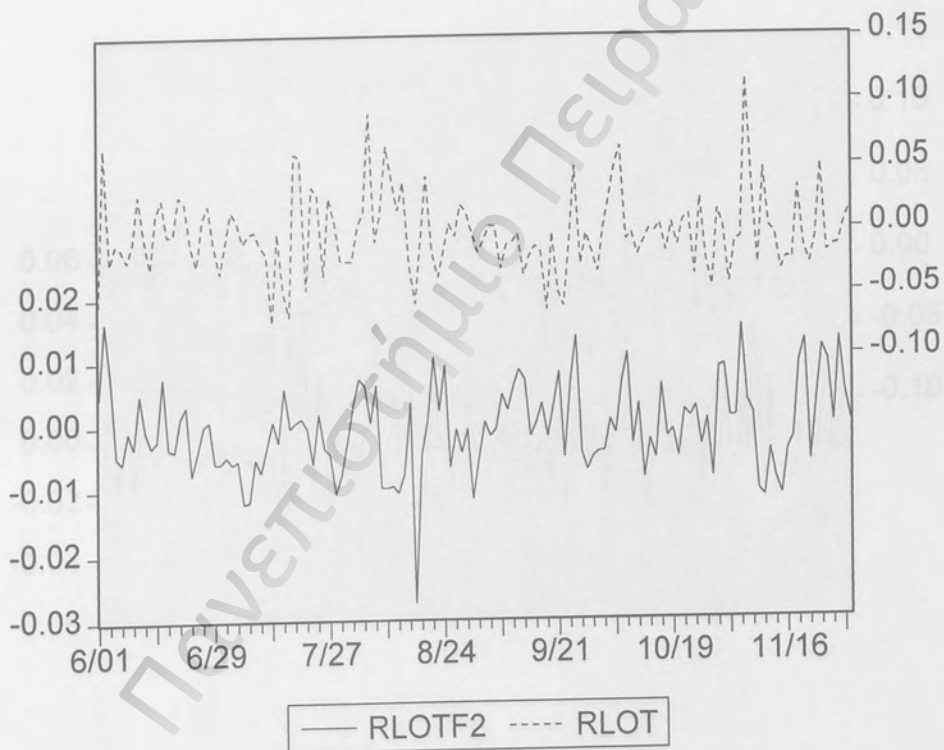
INTRALOT
Real and Forecasted Series
Dynamic forecast from 19/1/2000



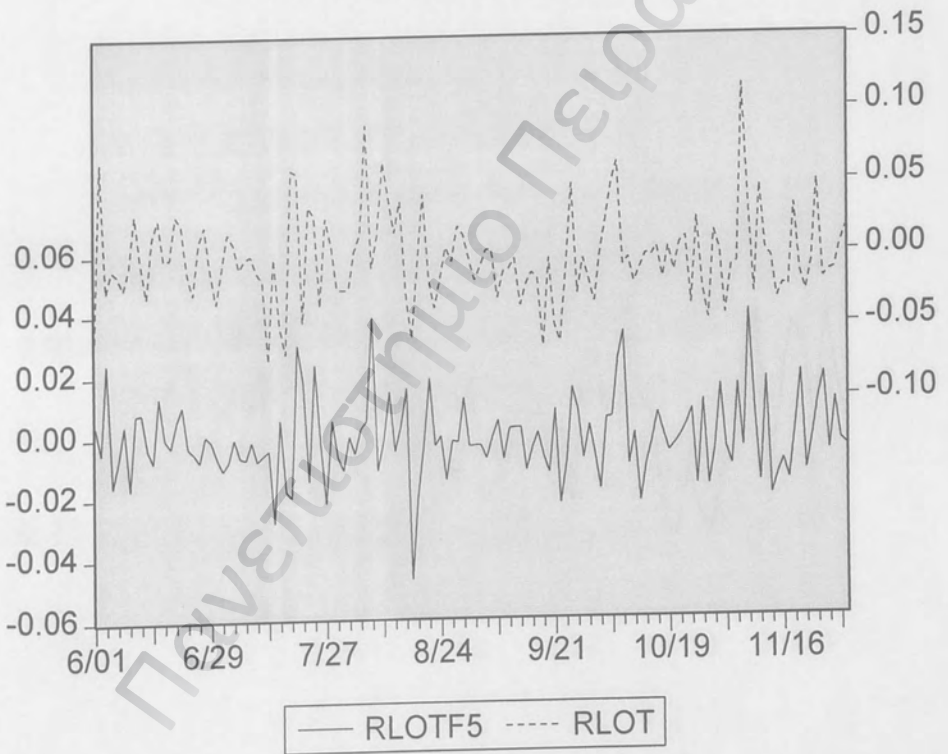
INTRALOT
Real and Forecasted series
Static Forecast from 19/1/2000



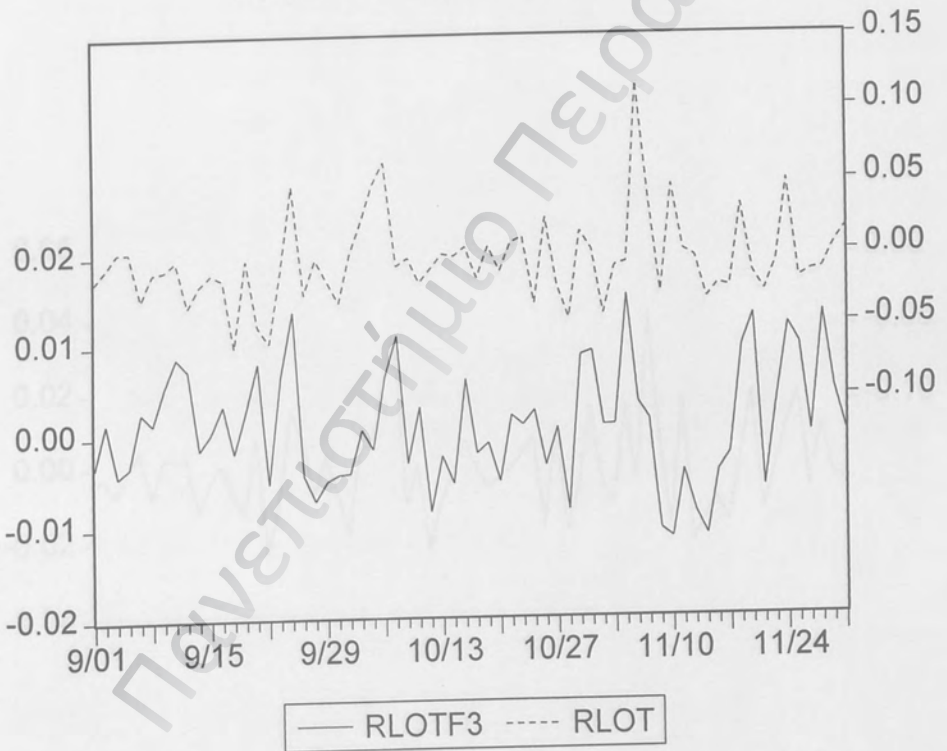
INTRALOT
Real and Forecasted series
Dynamic forecast from 26/6/2000



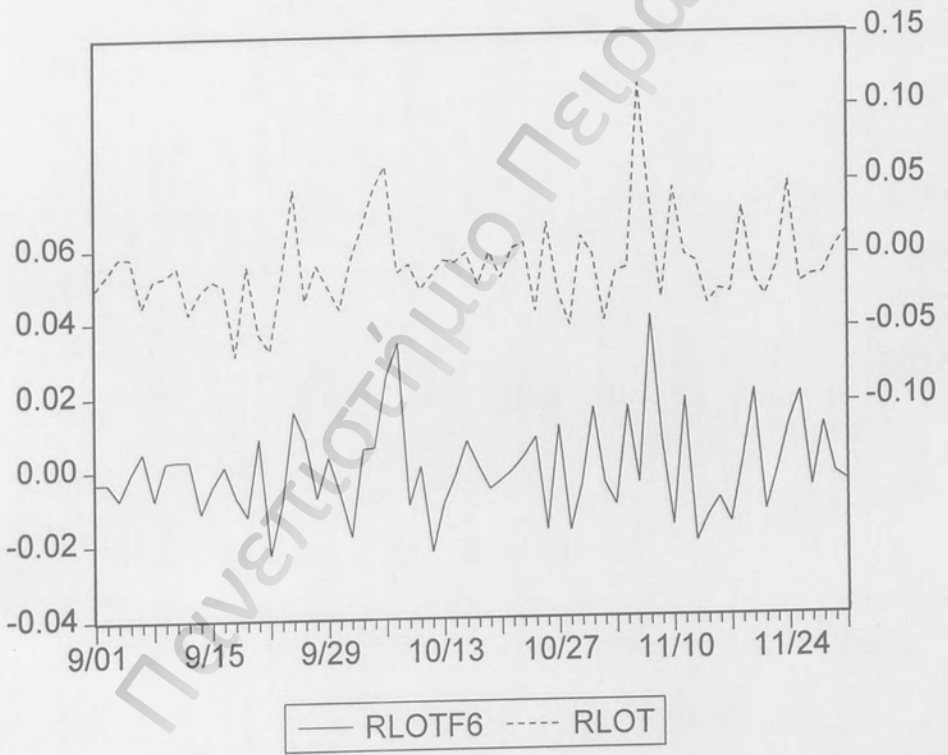
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Real and forecasted series
Static forecast from 26/6/2000



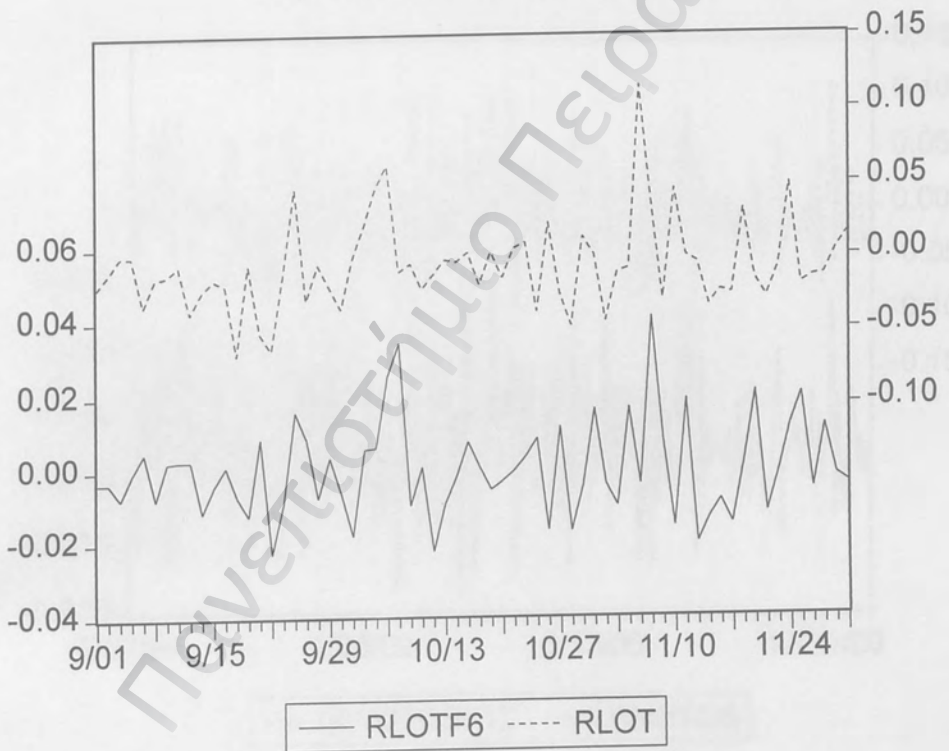
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Real and forecasted series
Dynamic forecast from 27/9/2000



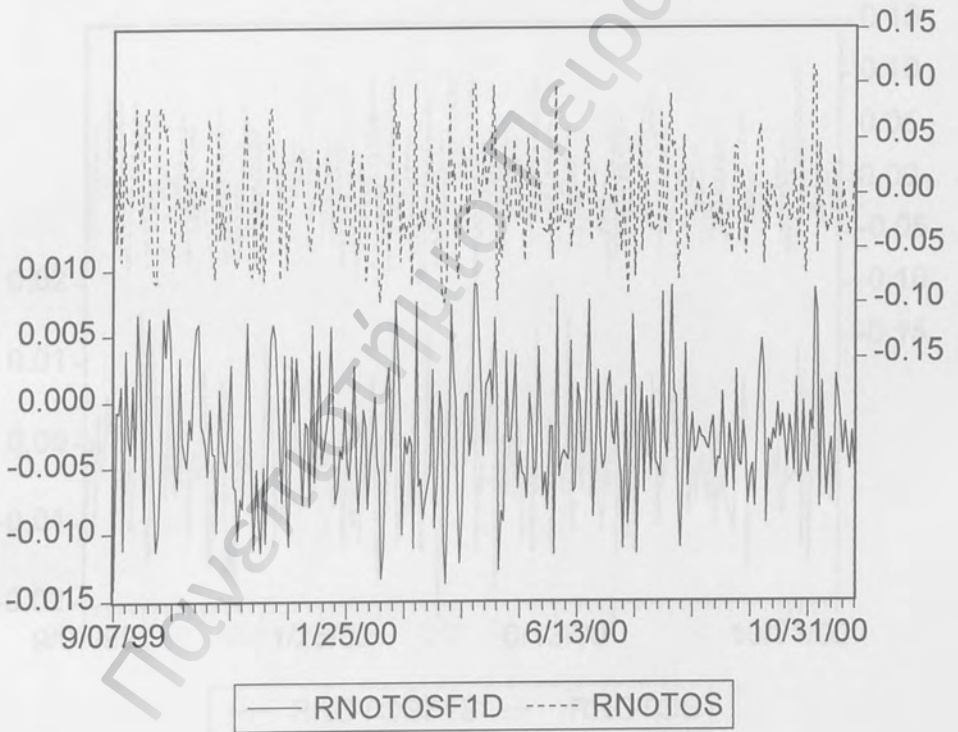
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Static forecast from 27/9/2000



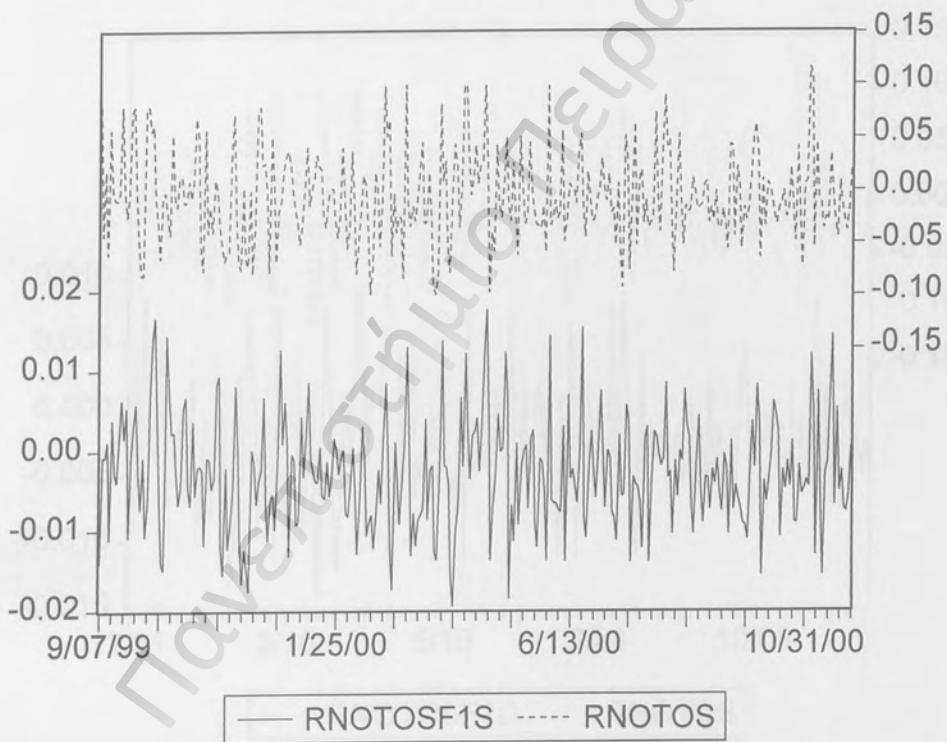
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Static forecast from 27/9/2000



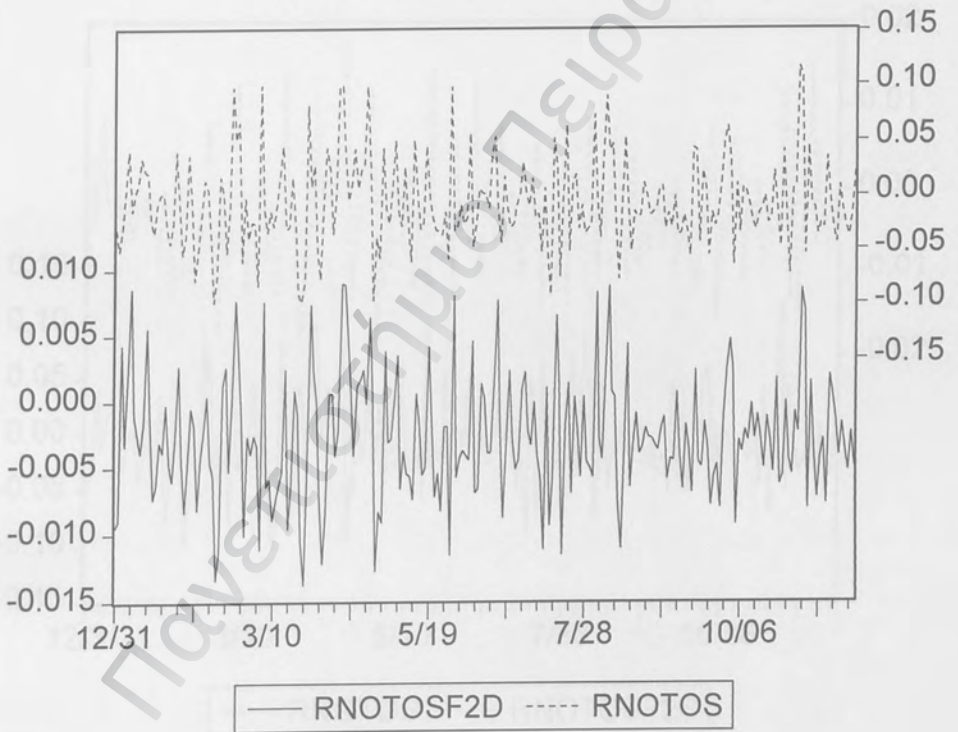
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Real and forecasted series
Dynamic forecast from 17/9/1999



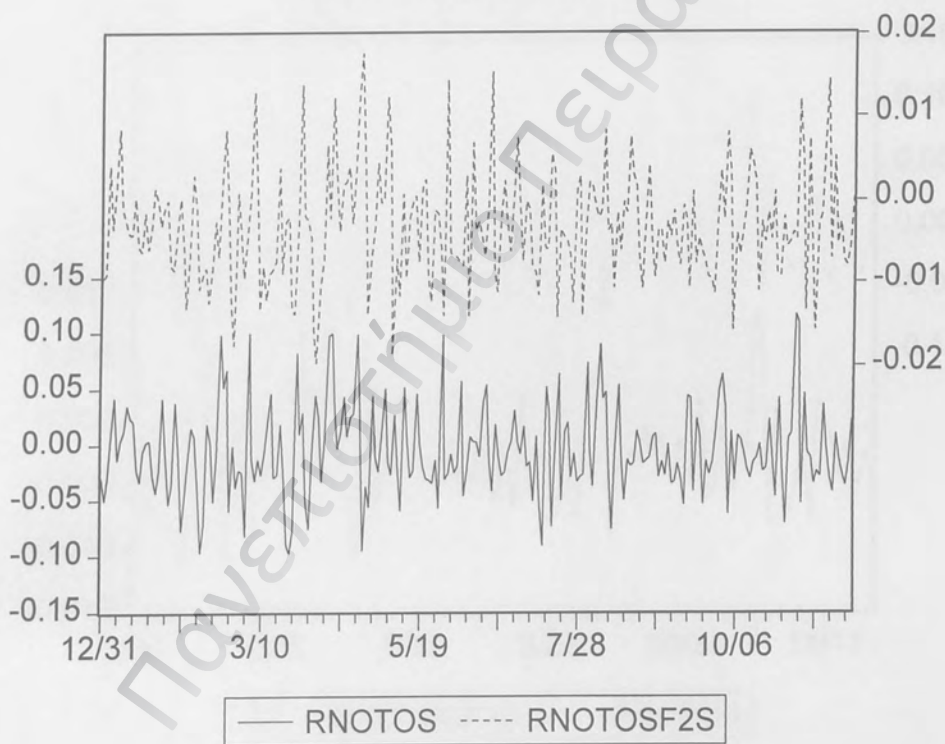
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Static forecasts from 17/9/1999



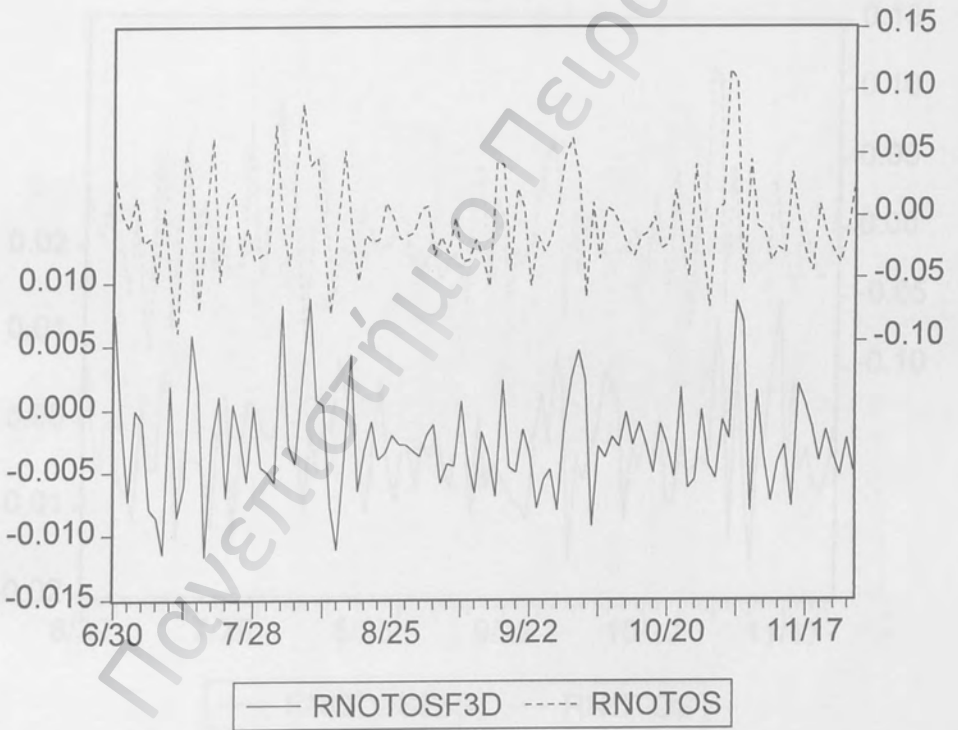
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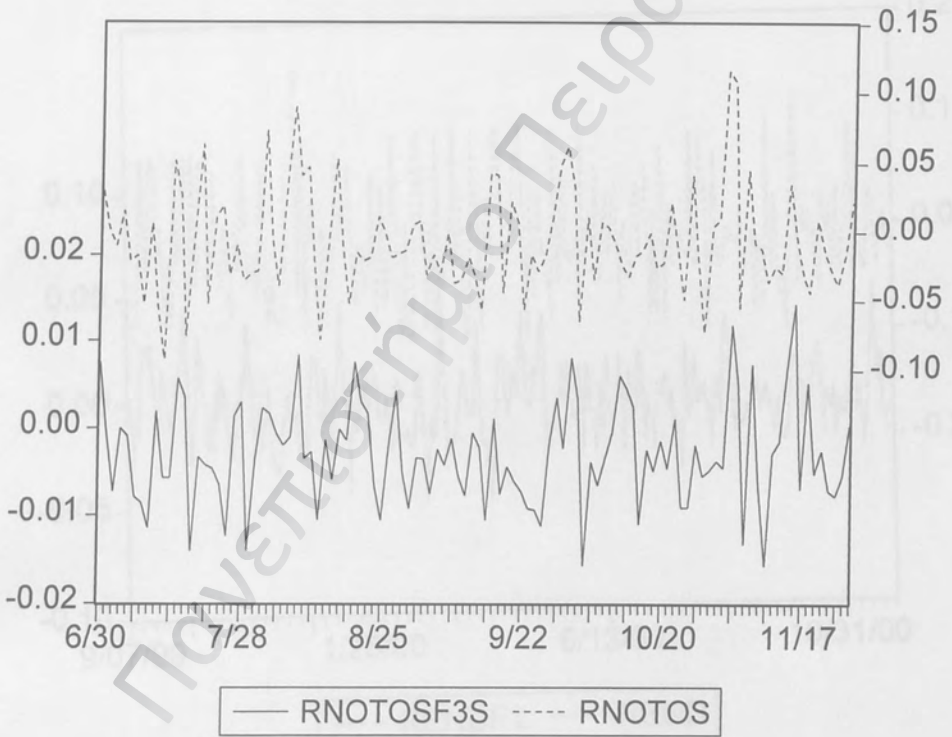
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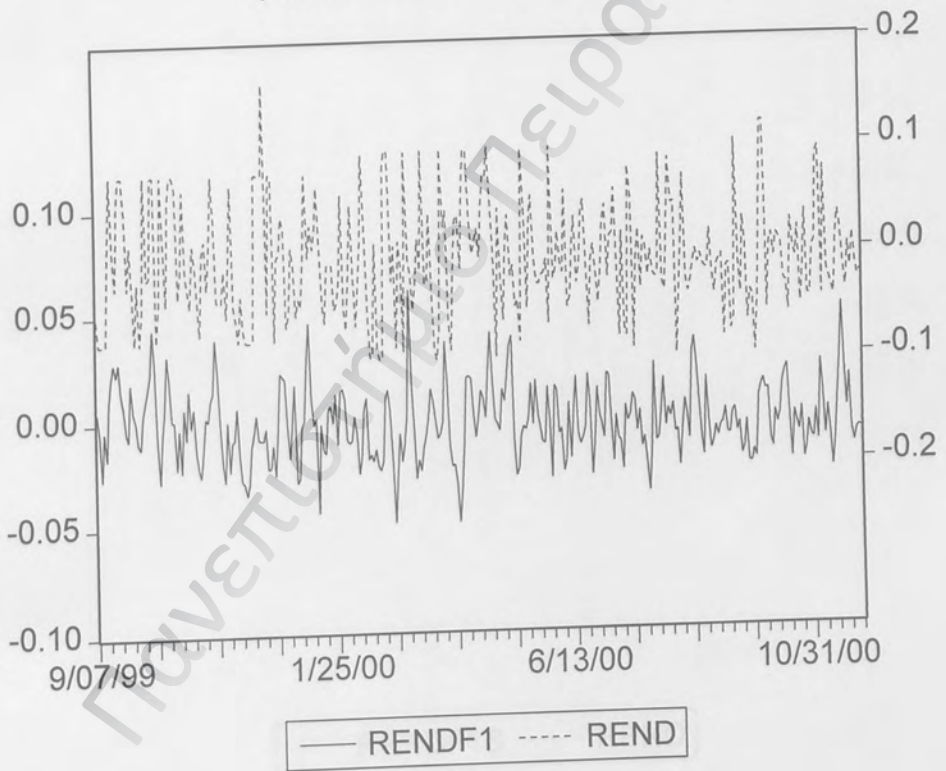
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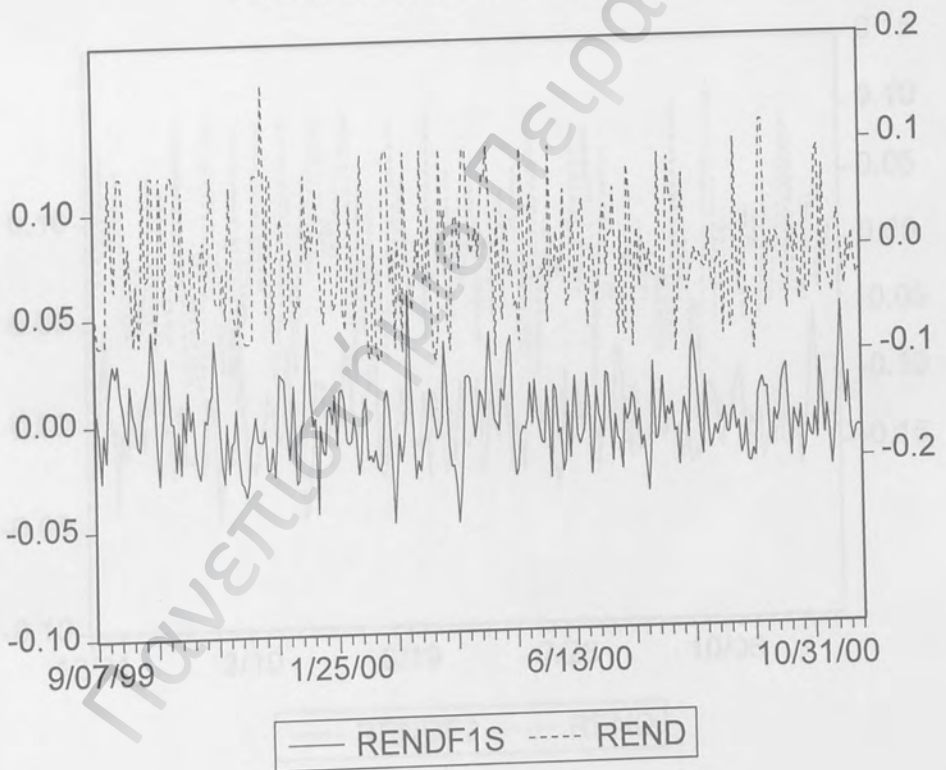
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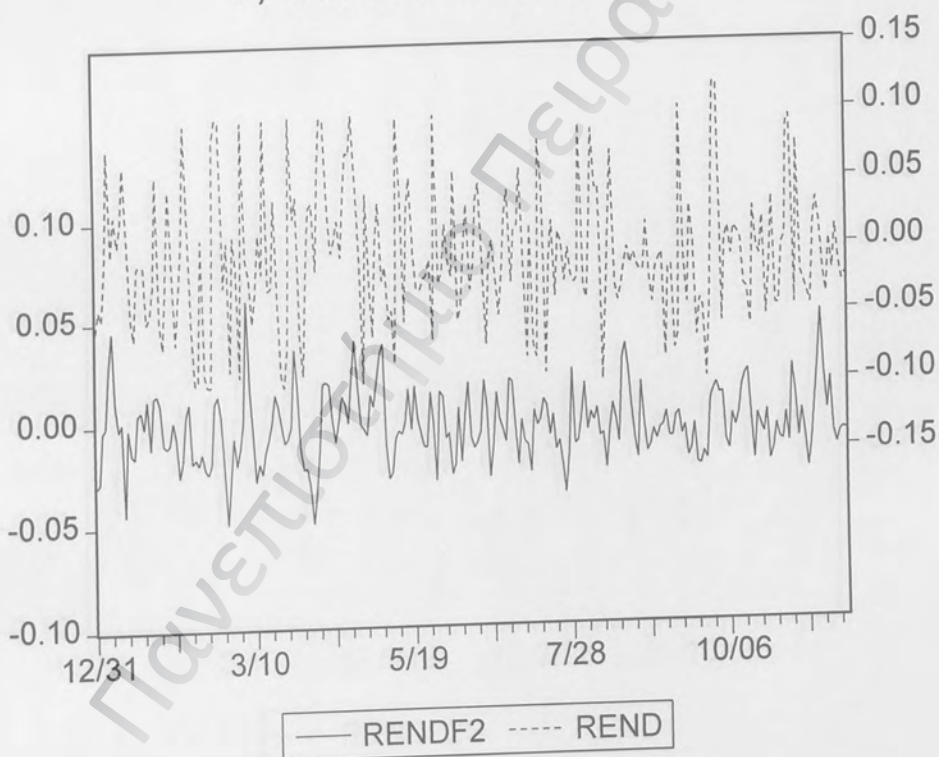
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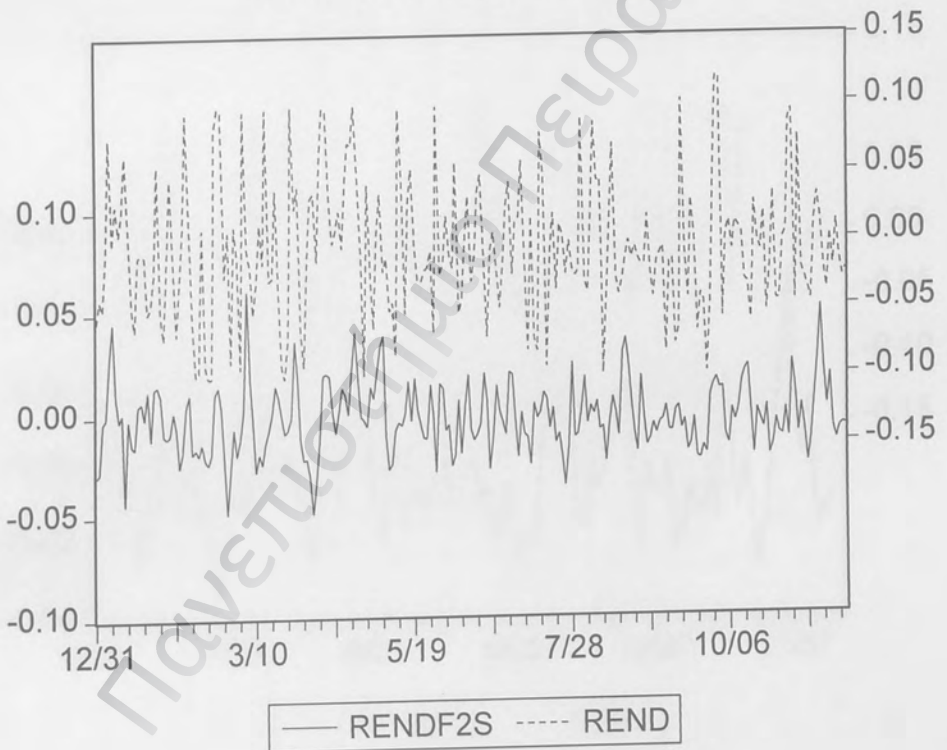
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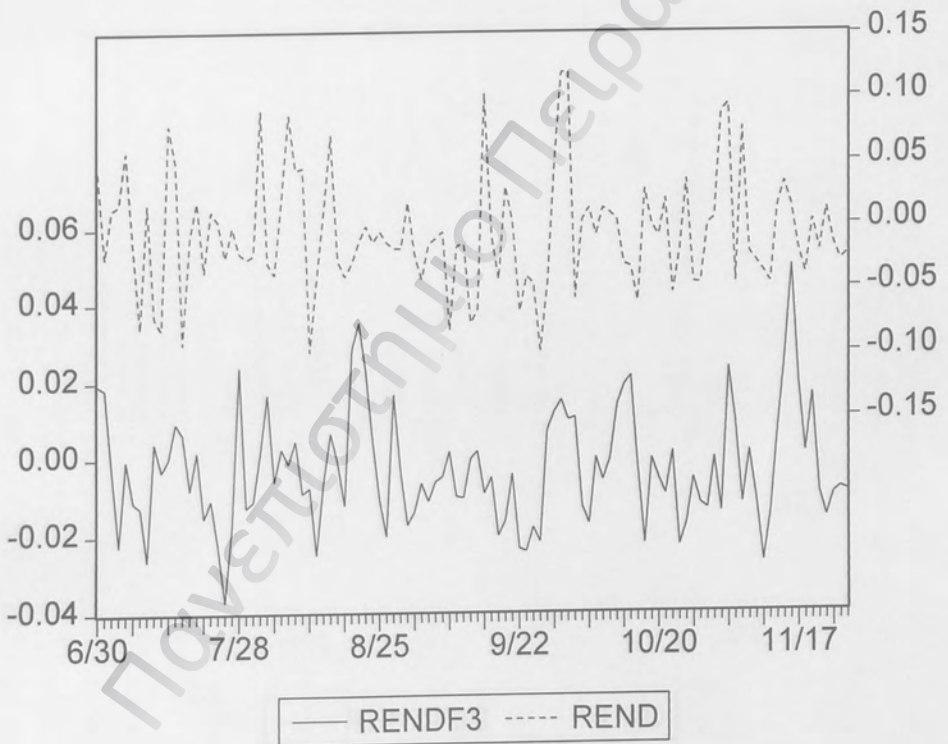
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Dynamic forecast from 19/1/2000



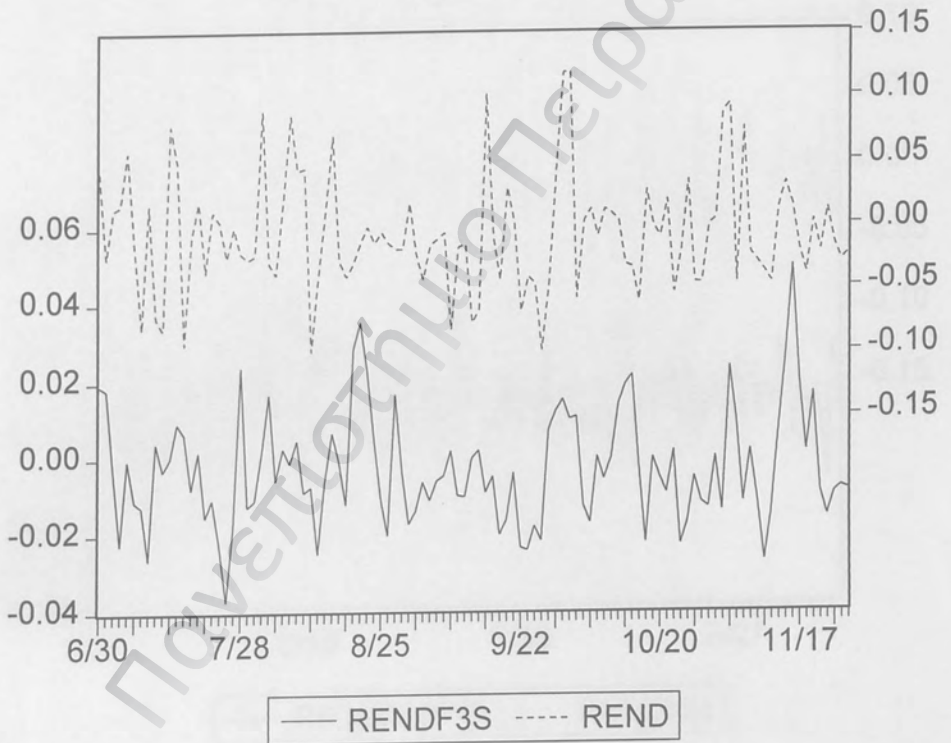
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Real and forecasted series
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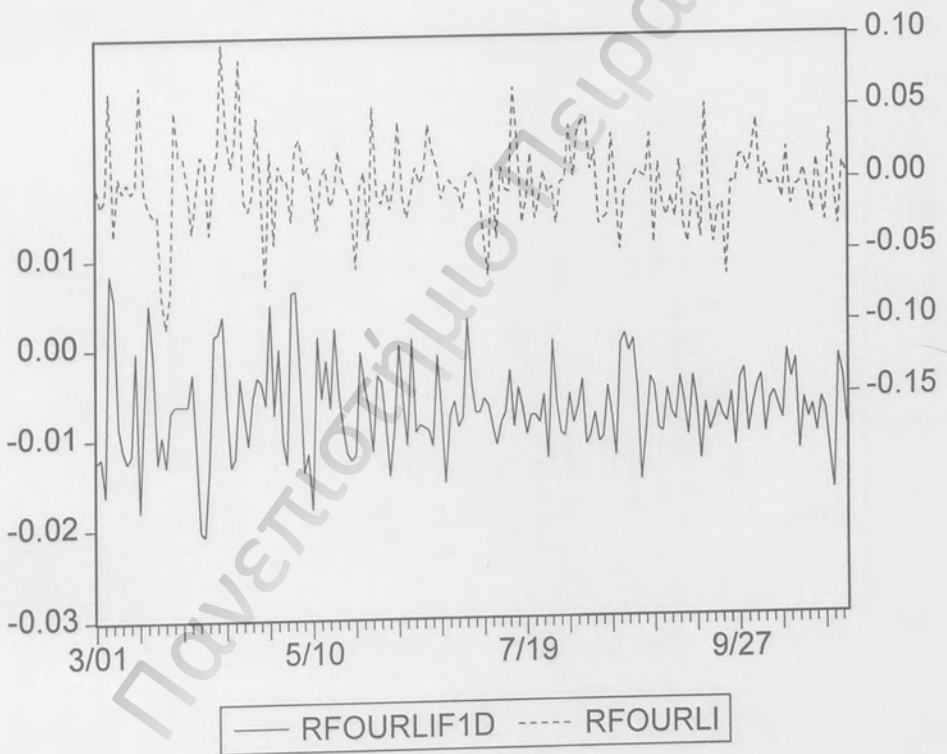
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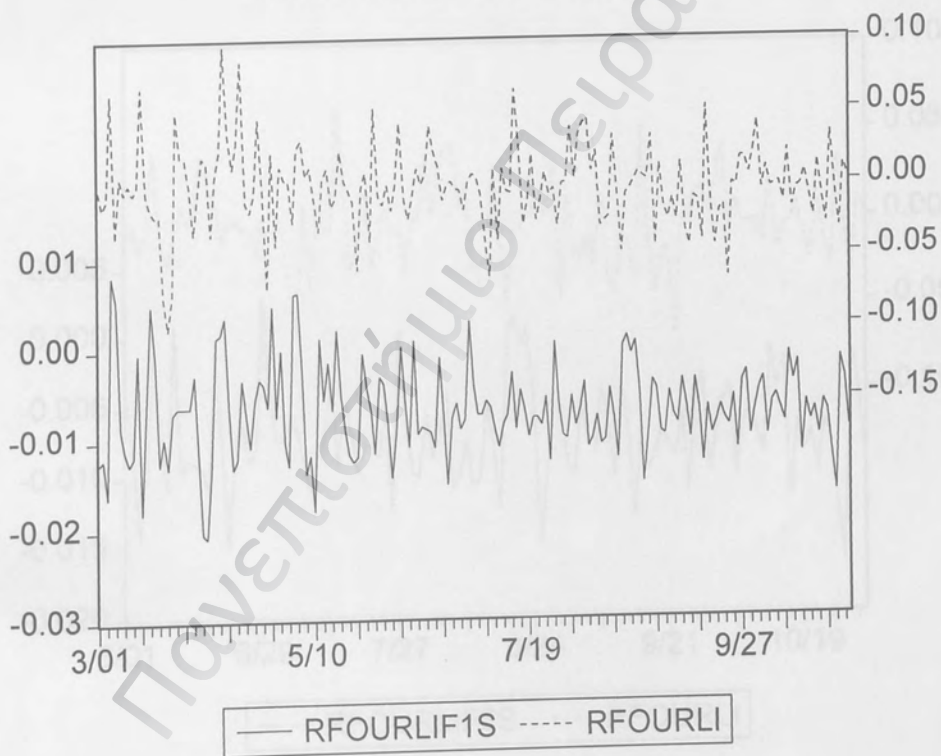
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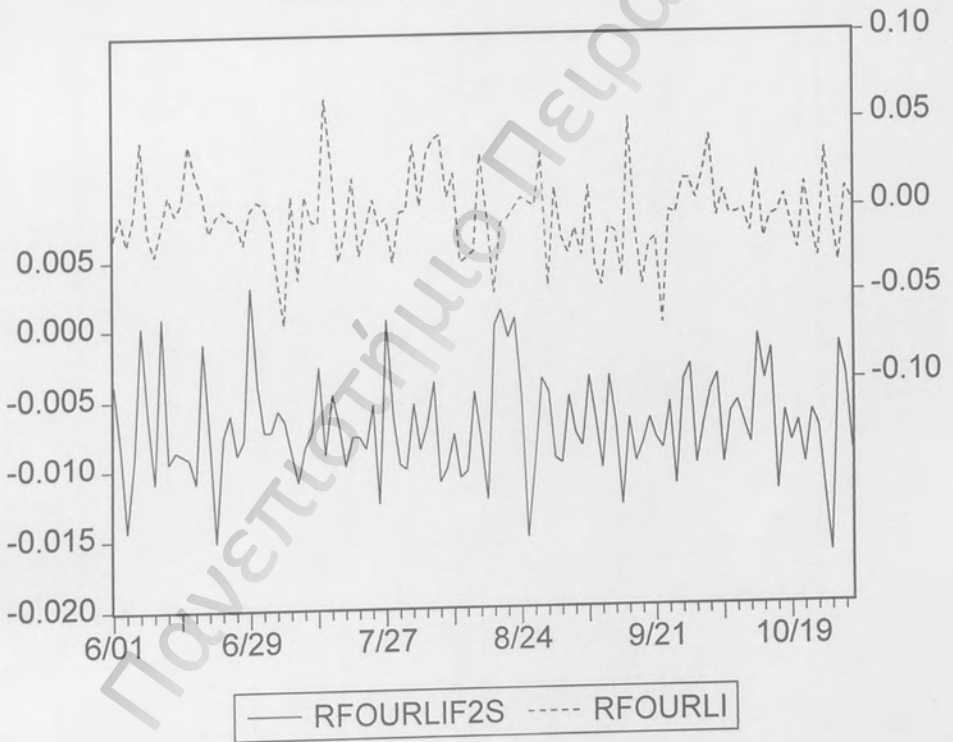
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Real and forecasted series
Dynamic forecast from 21/3/2000



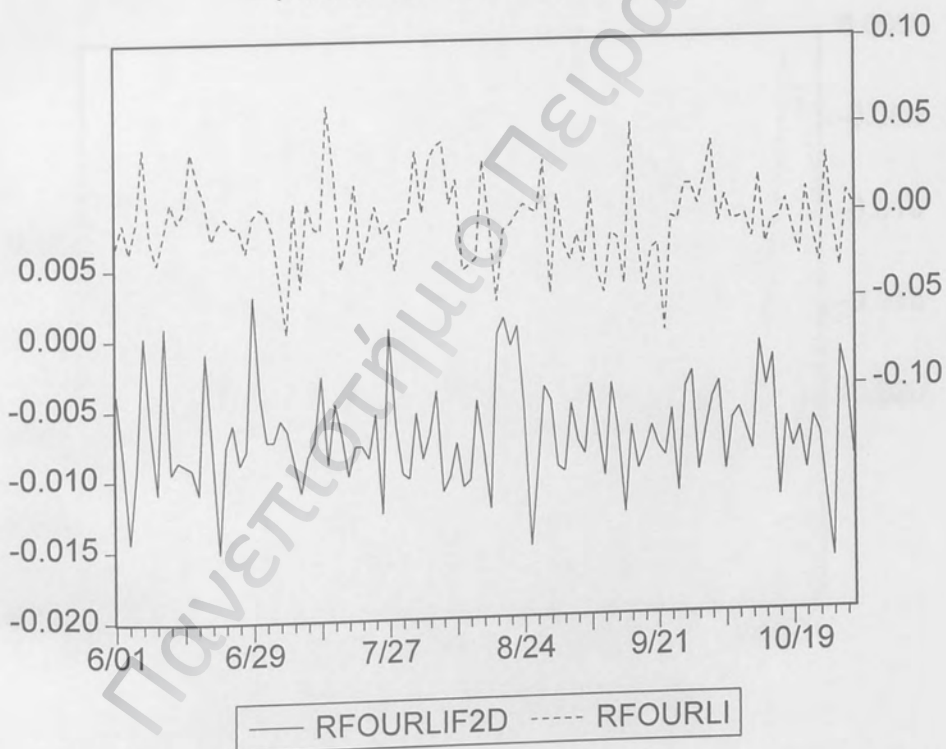
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Static forecast from 21/3/2000



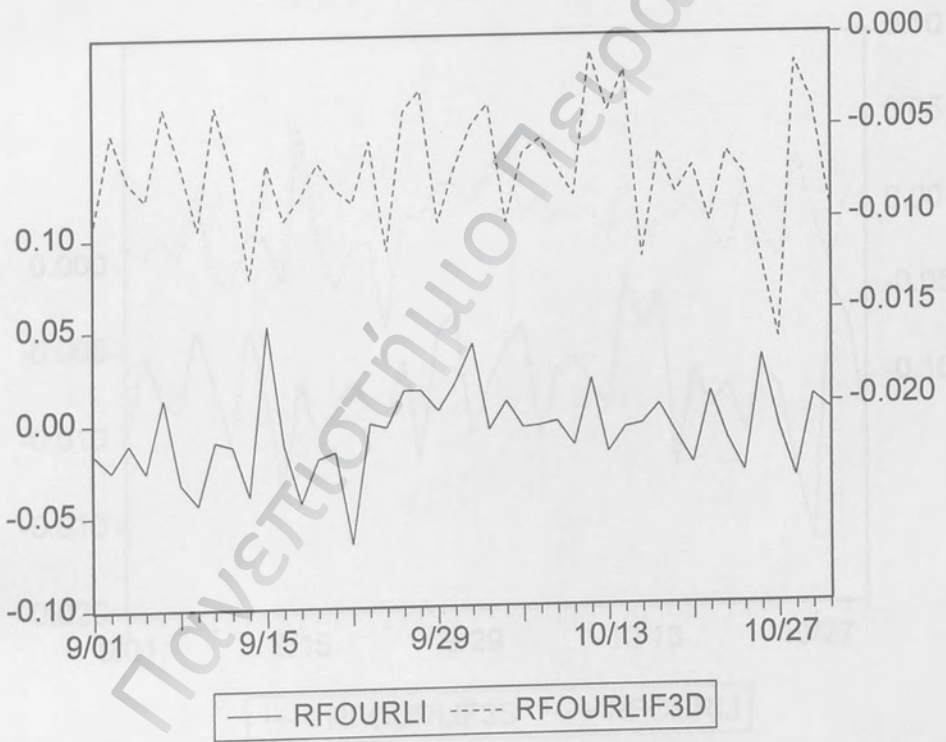
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Static forecast from 26/6/2000



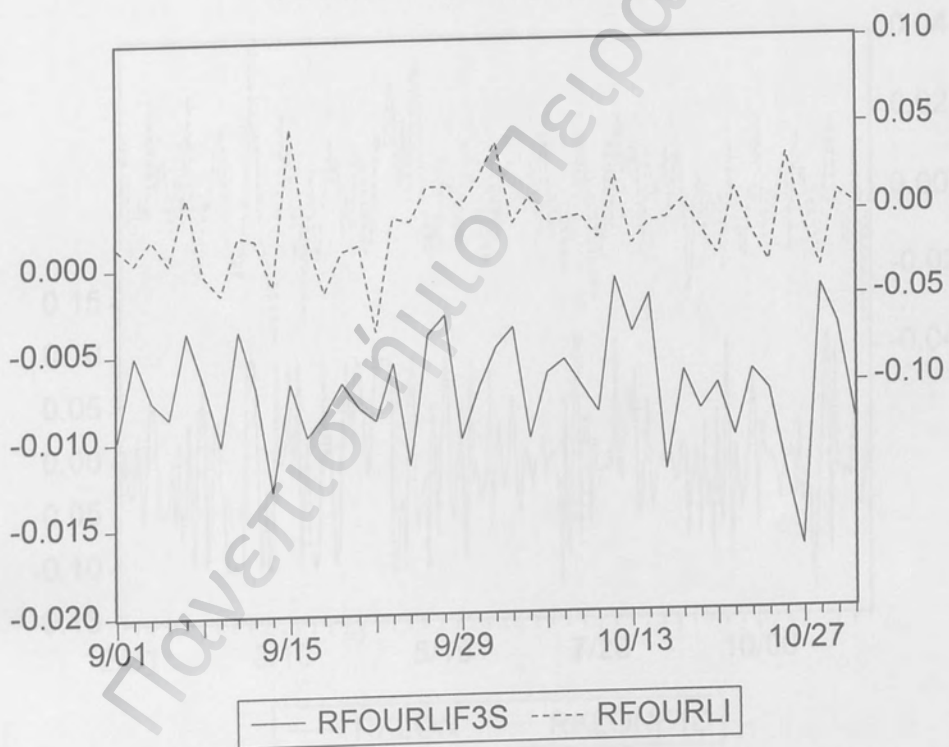
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Dynamic forecast from 26/6/2000



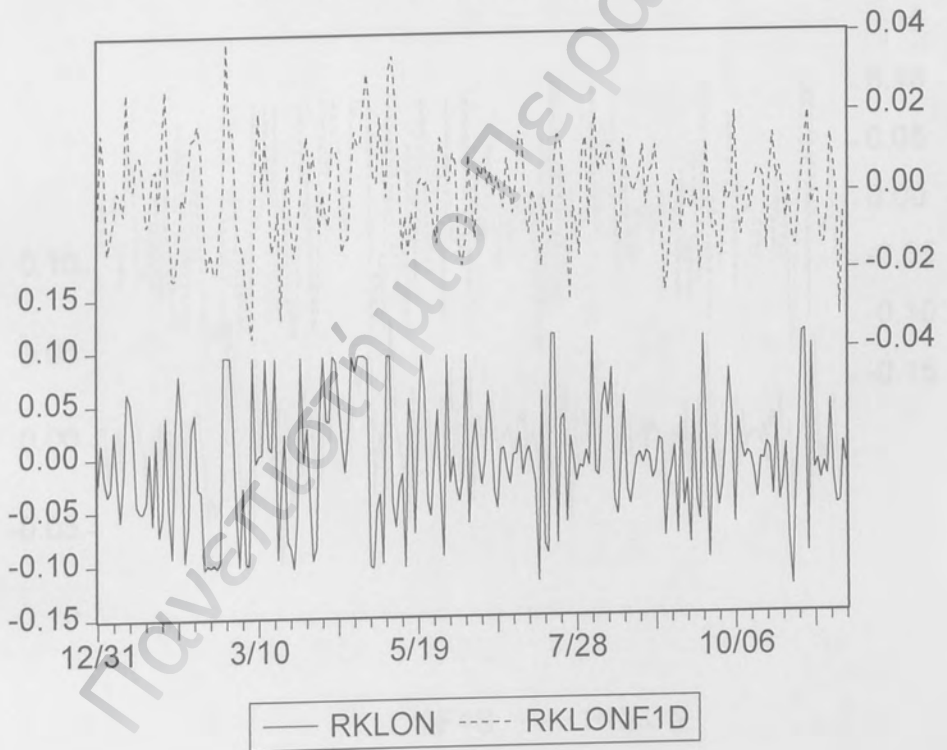
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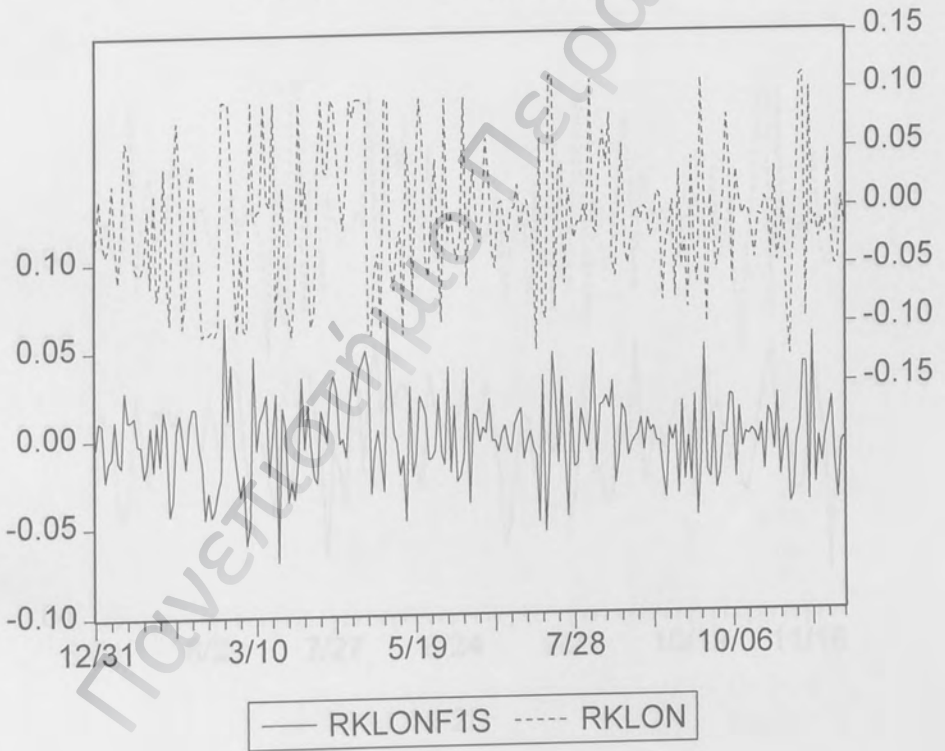
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Static forecast from 27/9/2000



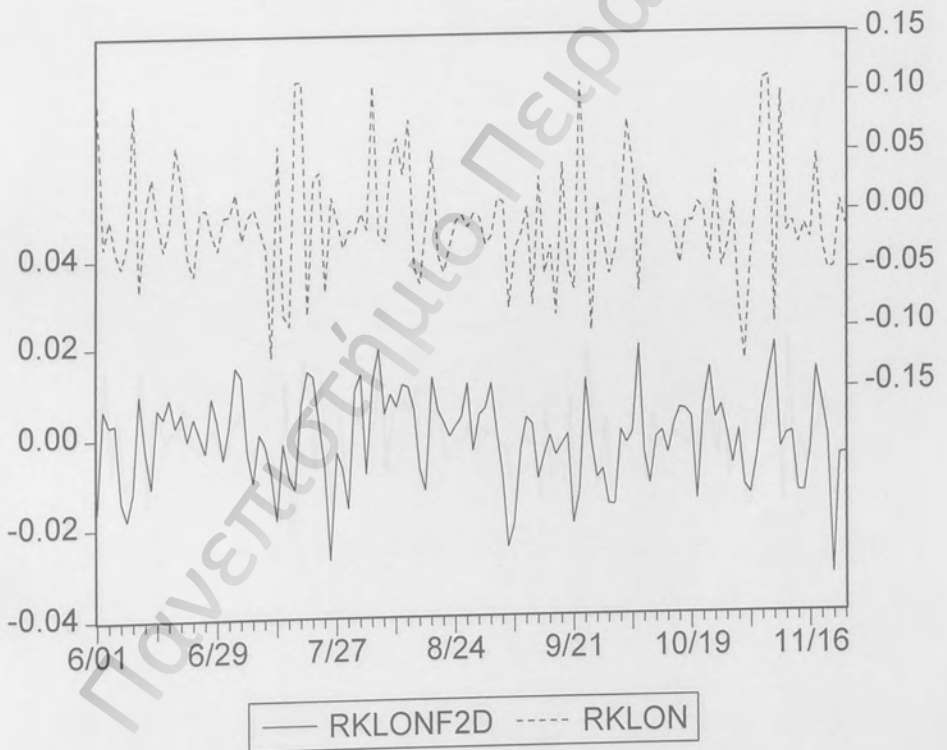
KLONATEX
Real and forecasted series
Dynamic forecast from 19/1/2000



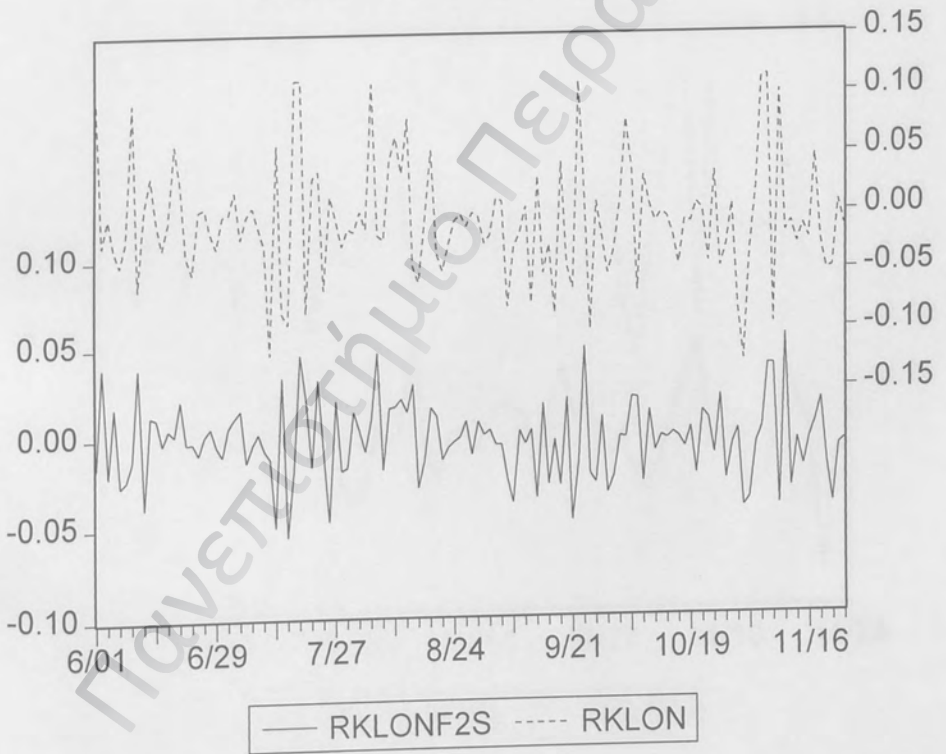
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Static forecast from 19/1/2000



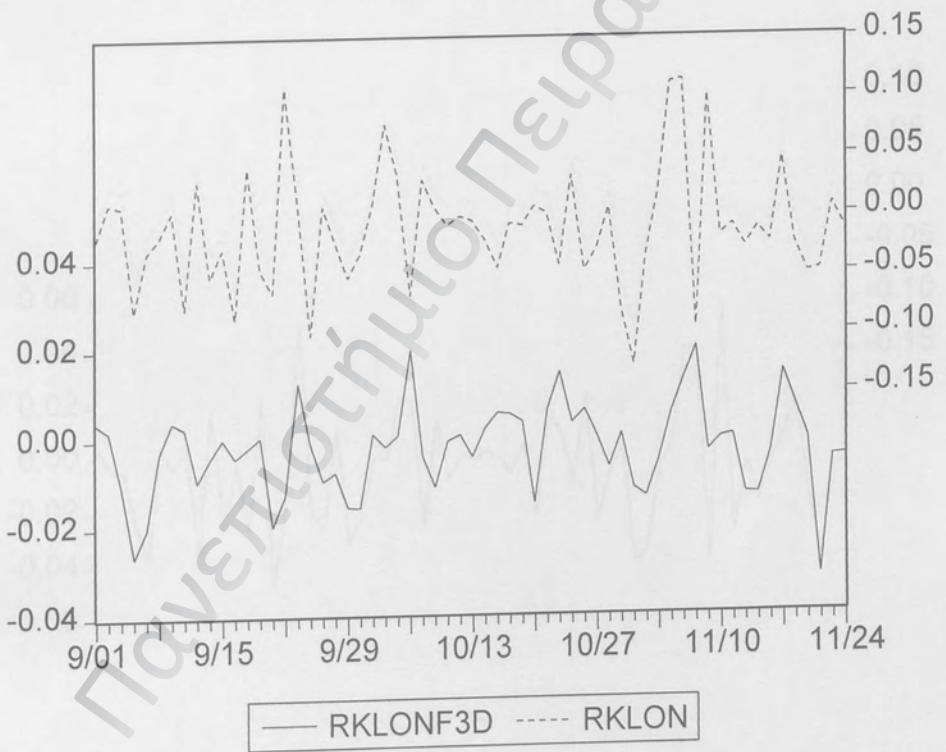
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Dynamic forecast from 26/6/2000



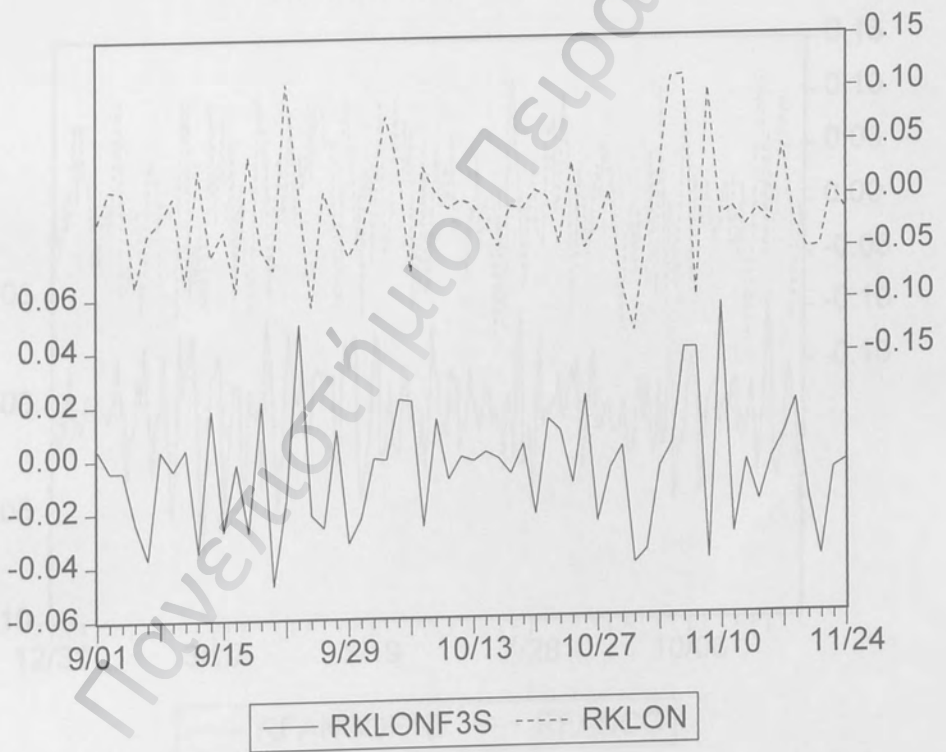
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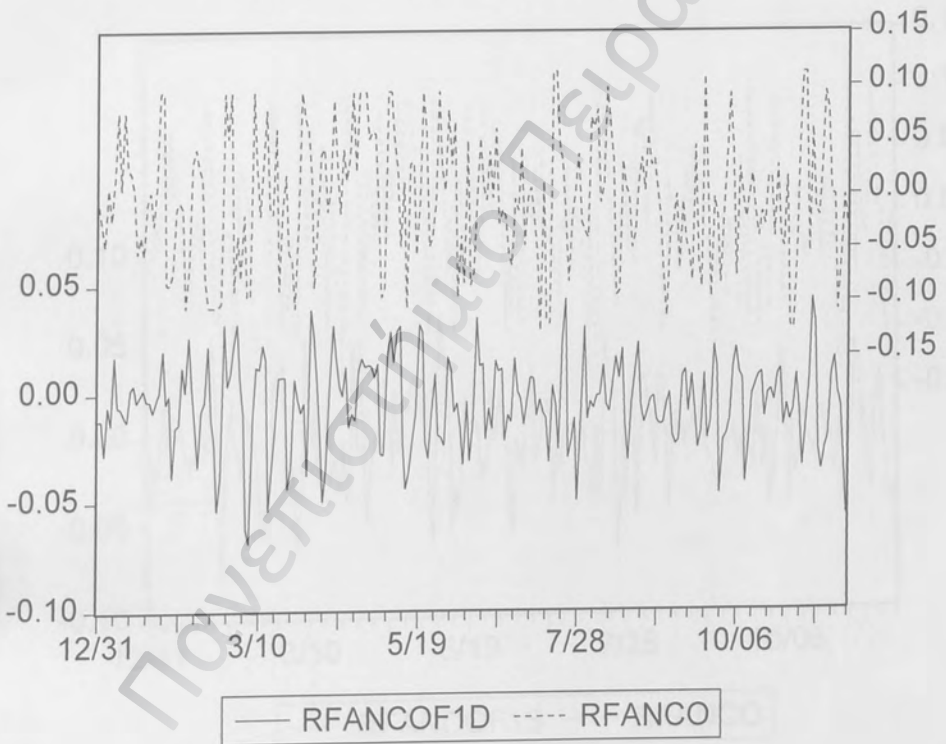
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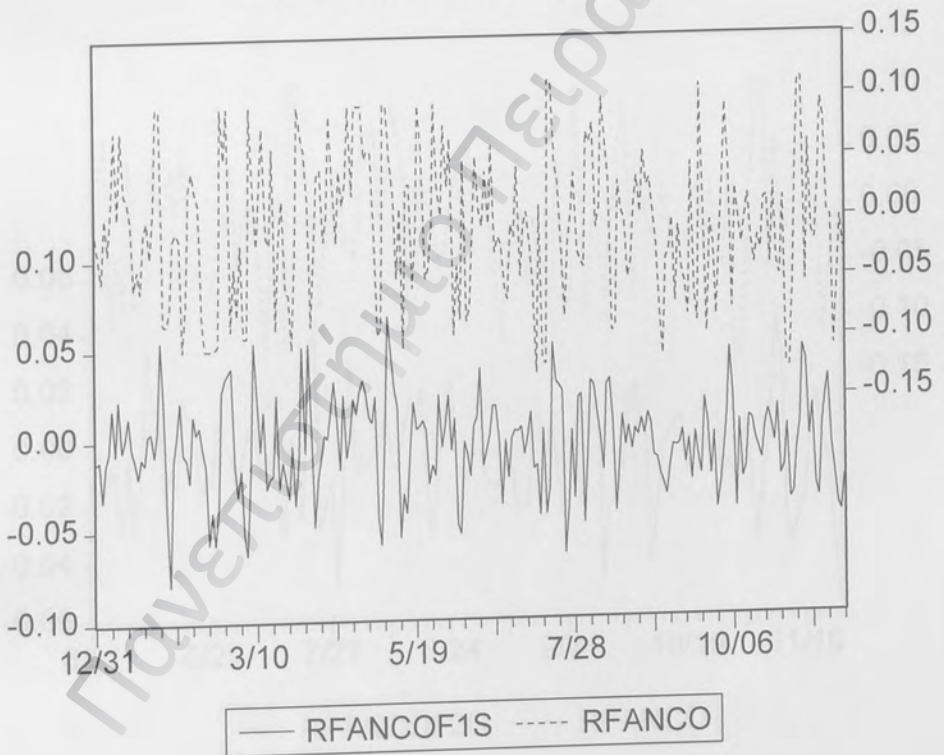
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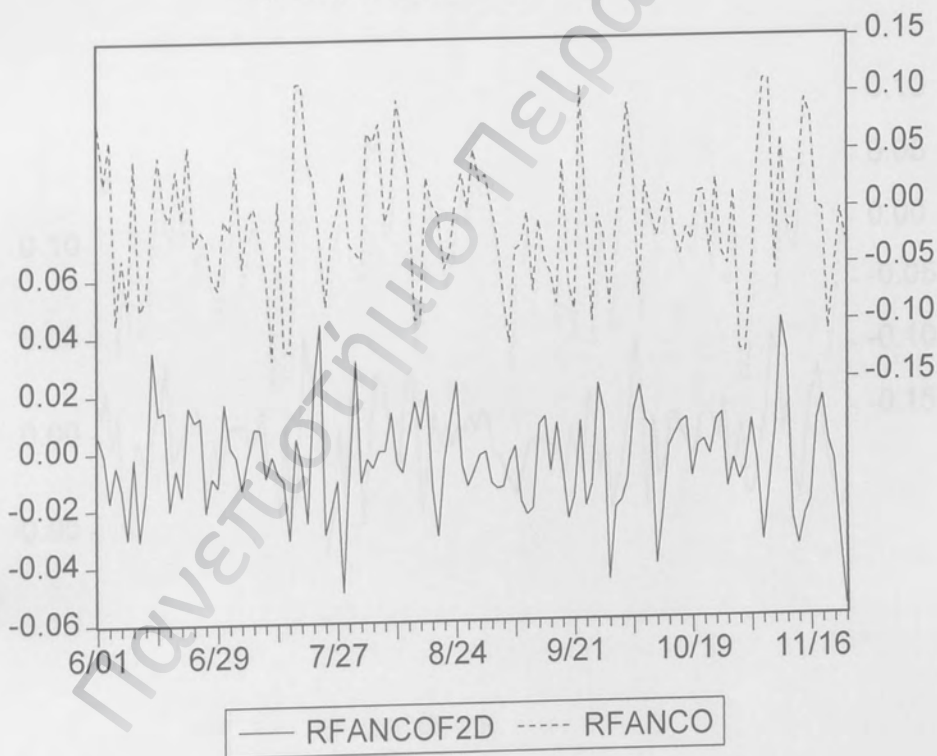
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Dynamic forecast from 19/1/2000



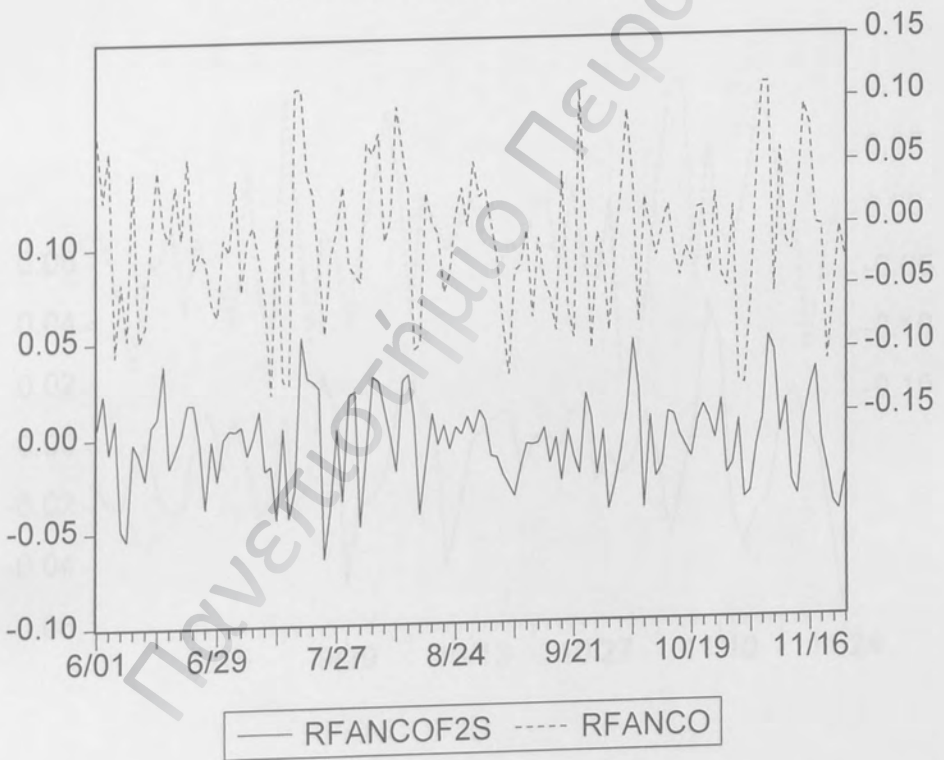
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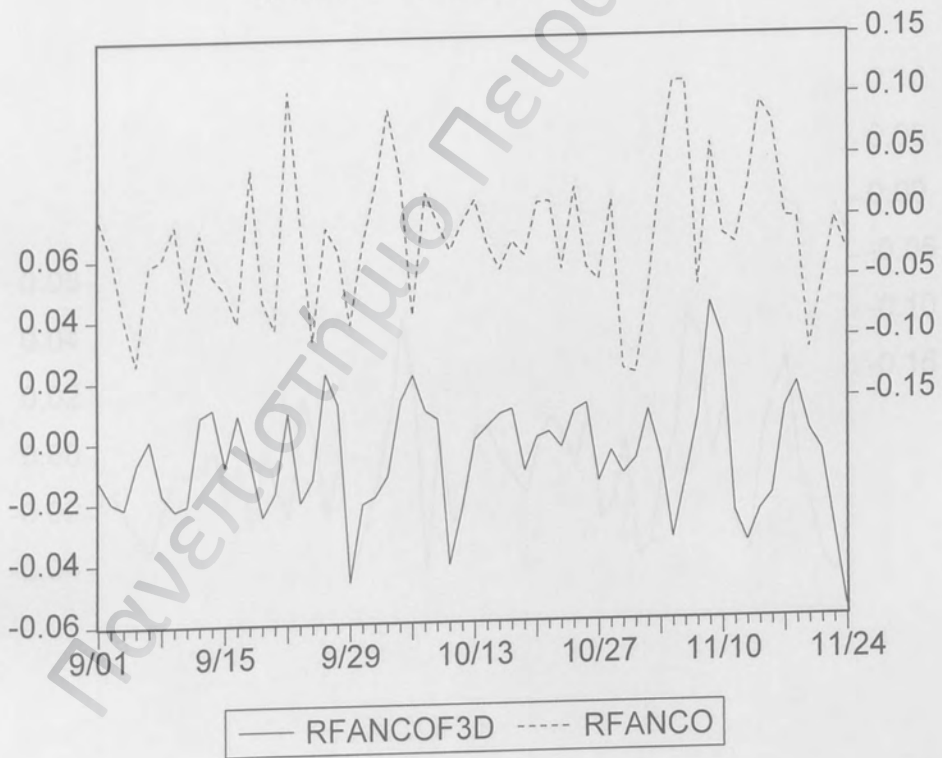
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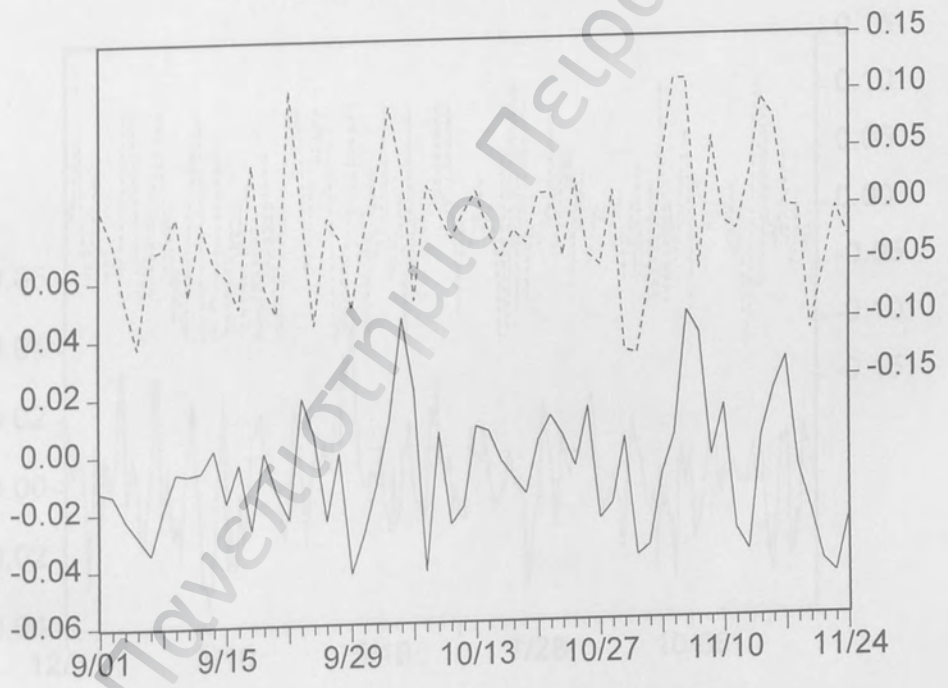
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Static forecast from 26/6/2000



FANCO
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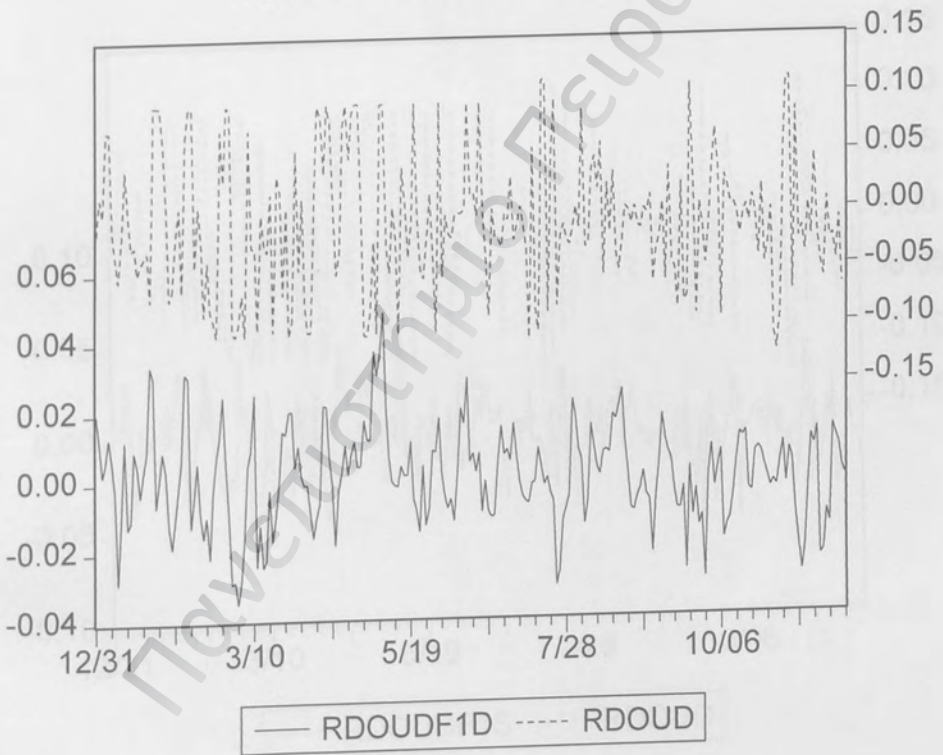


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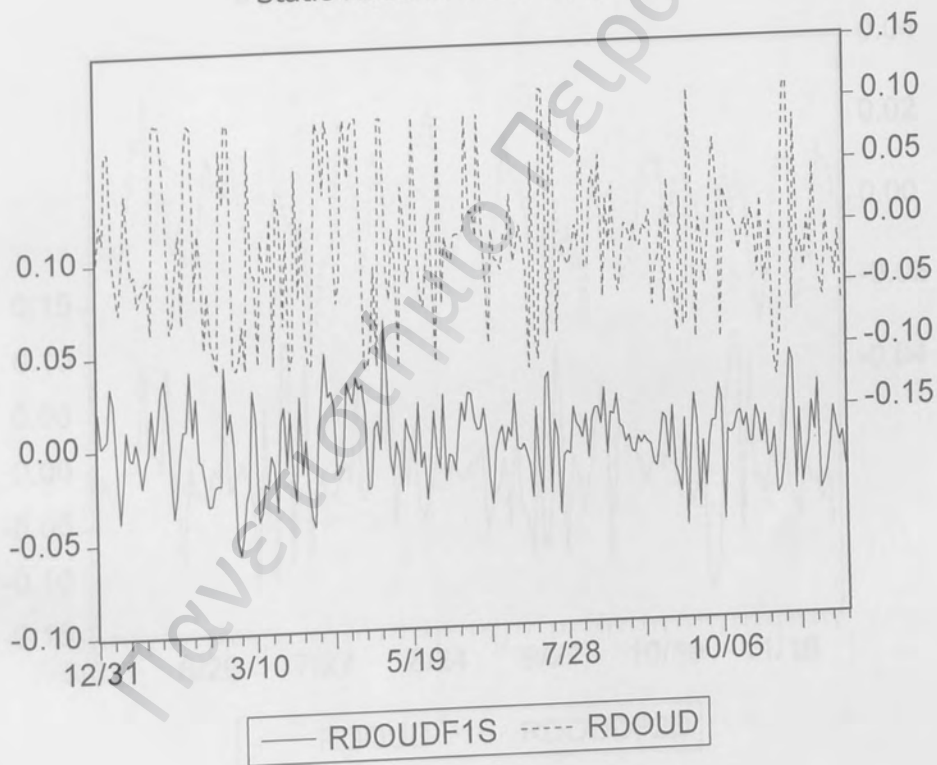


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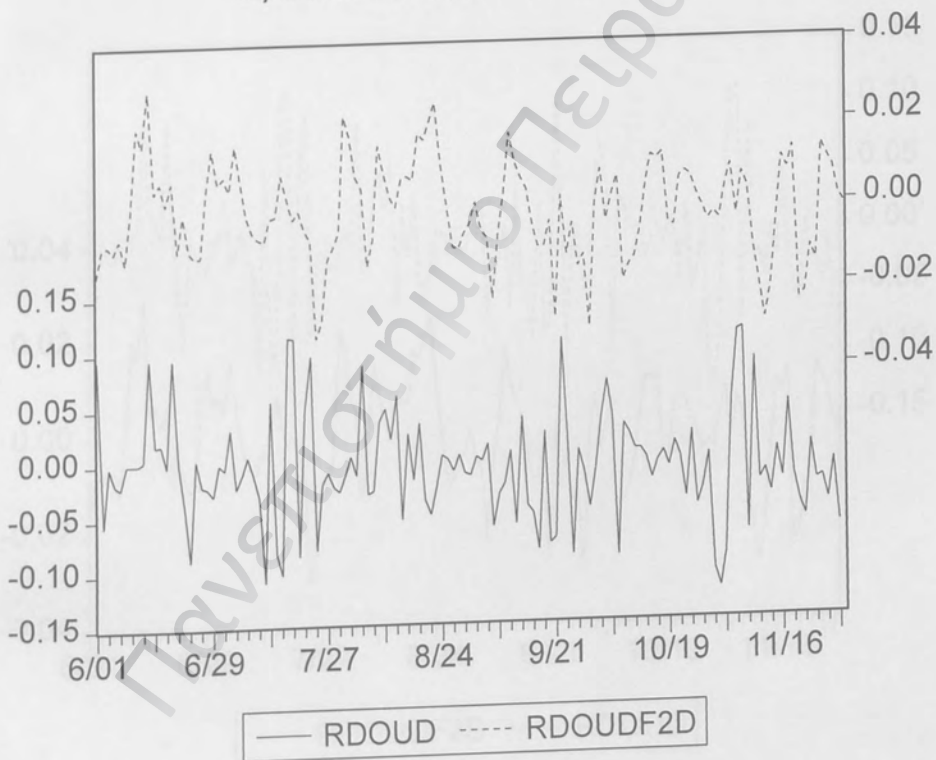
DOUDOS
Real and forecasted series
Dynamic forecast from 19/1/2000



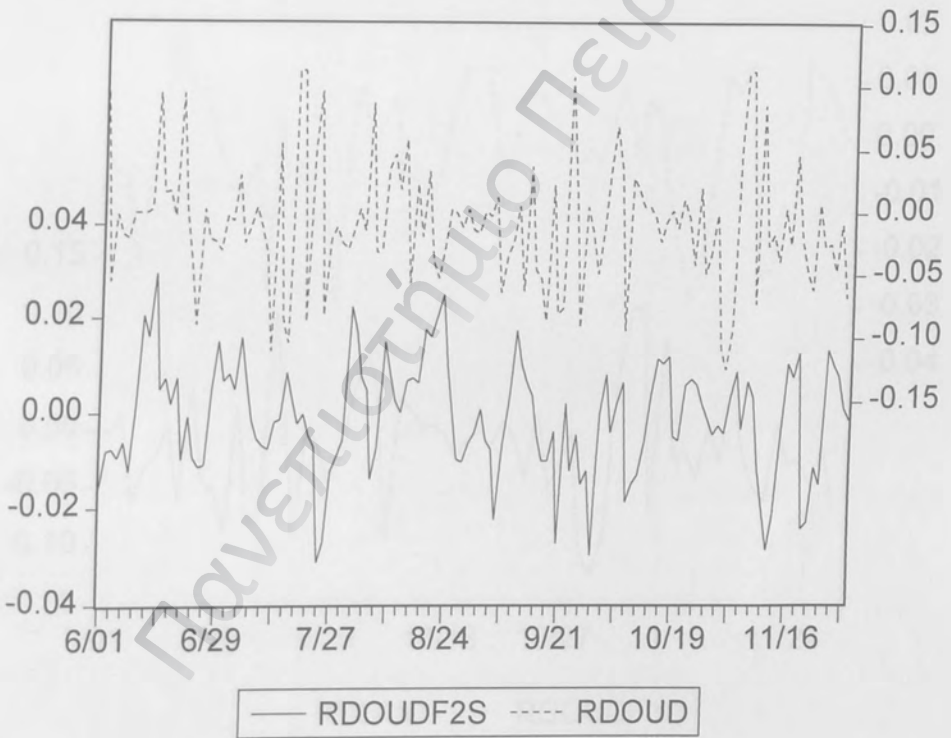
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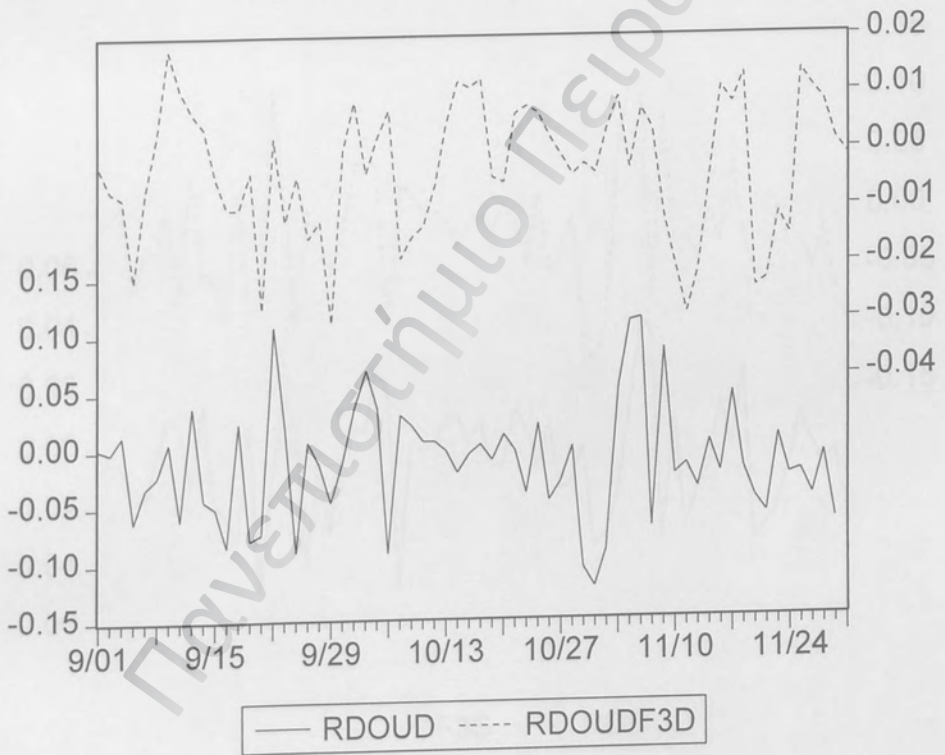
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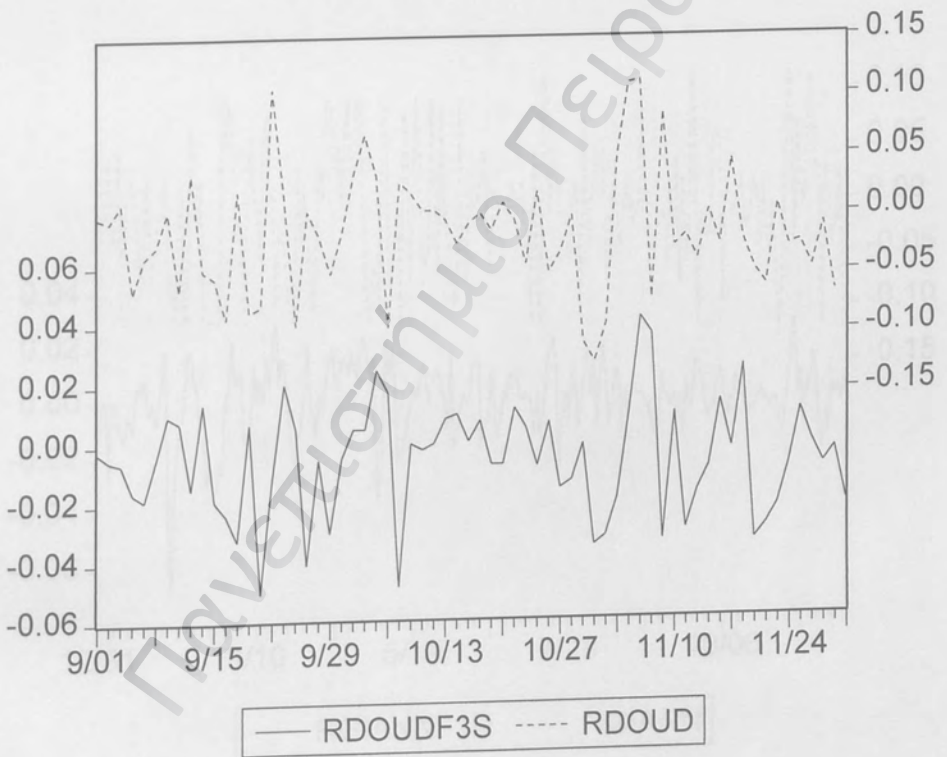
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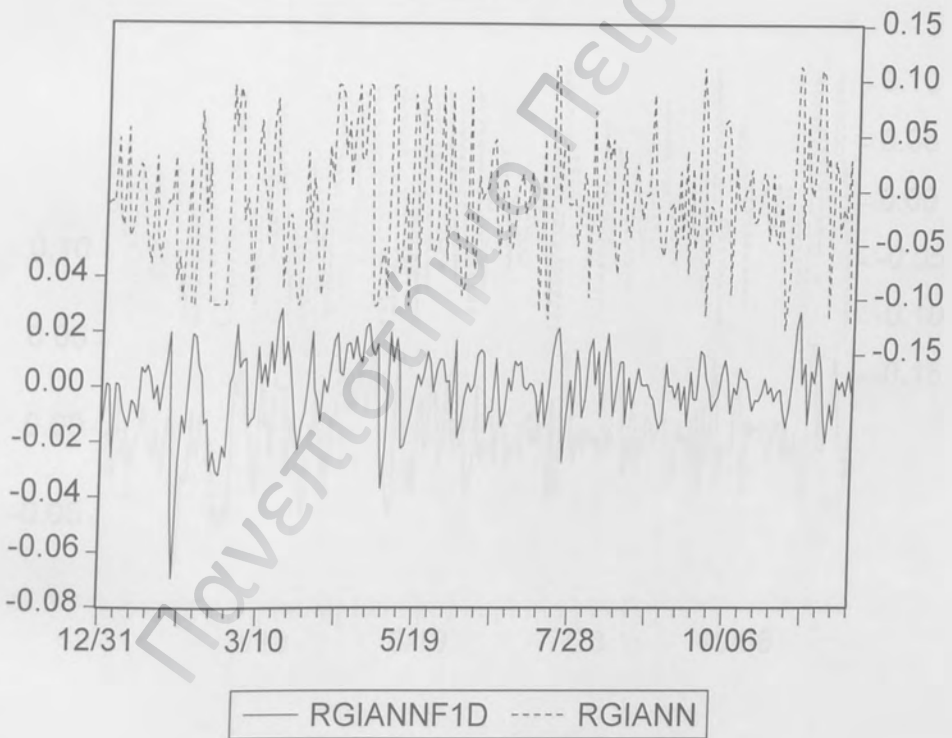
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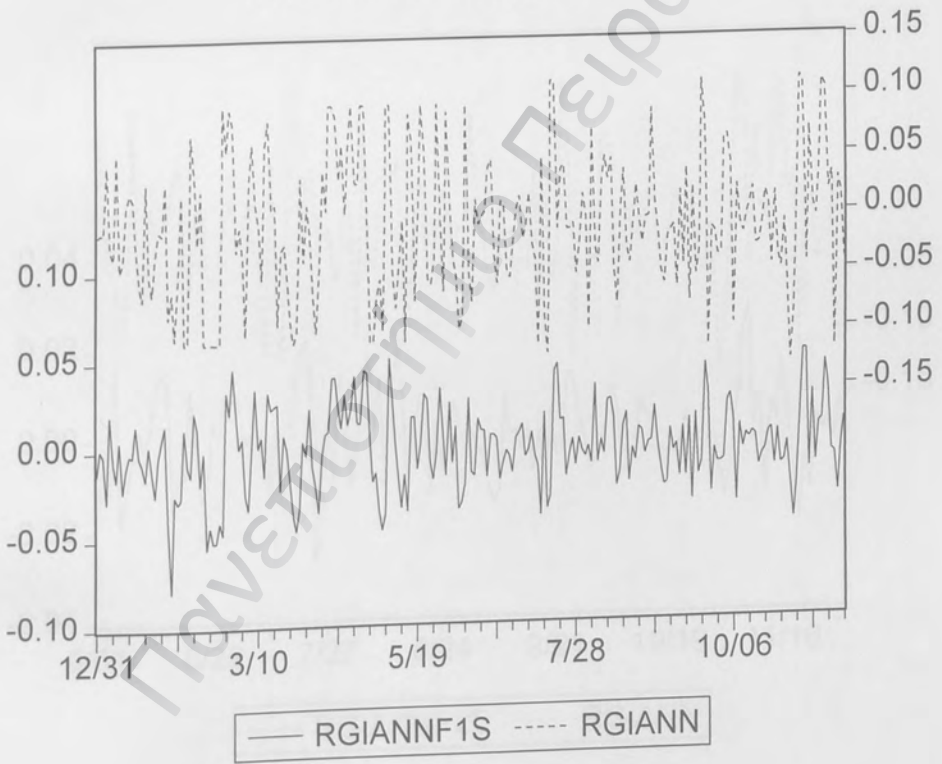
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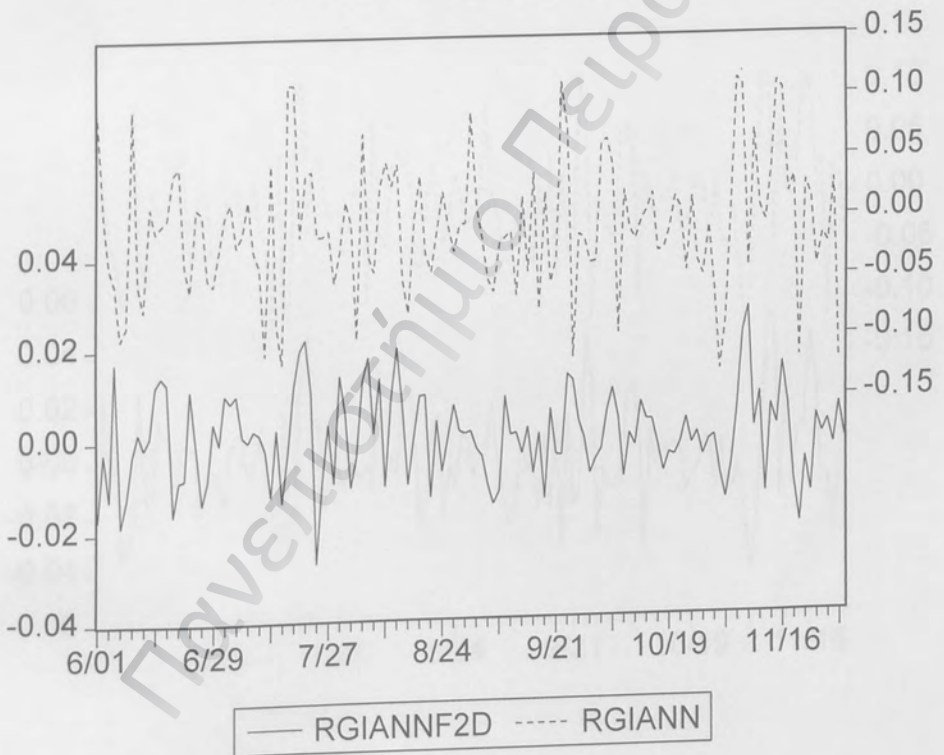
GIANNOUSIS
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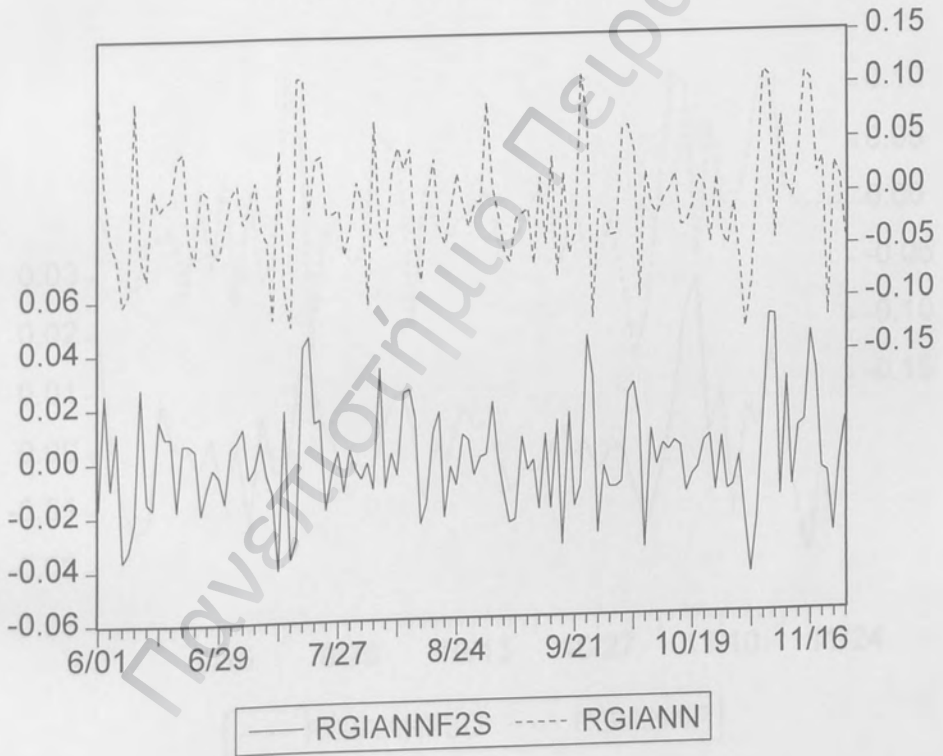
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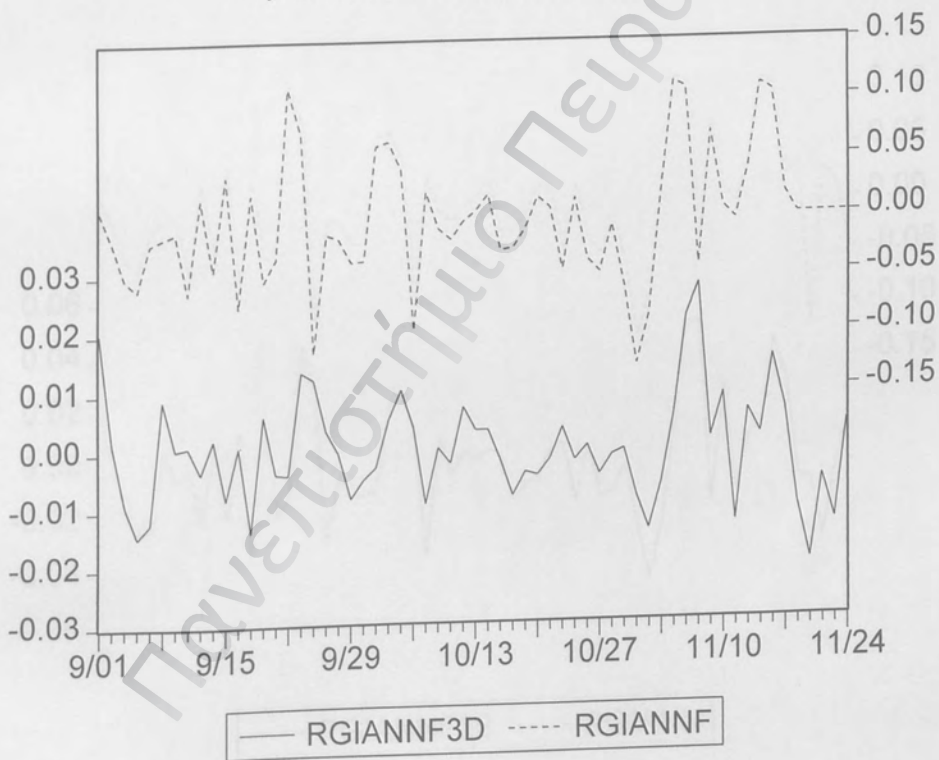
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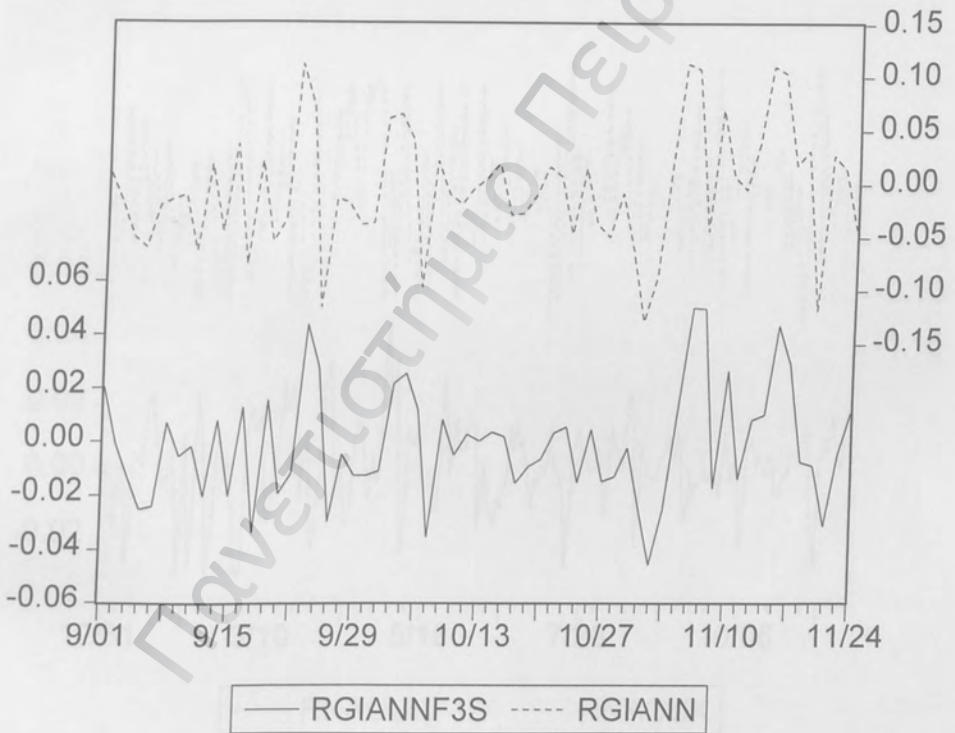
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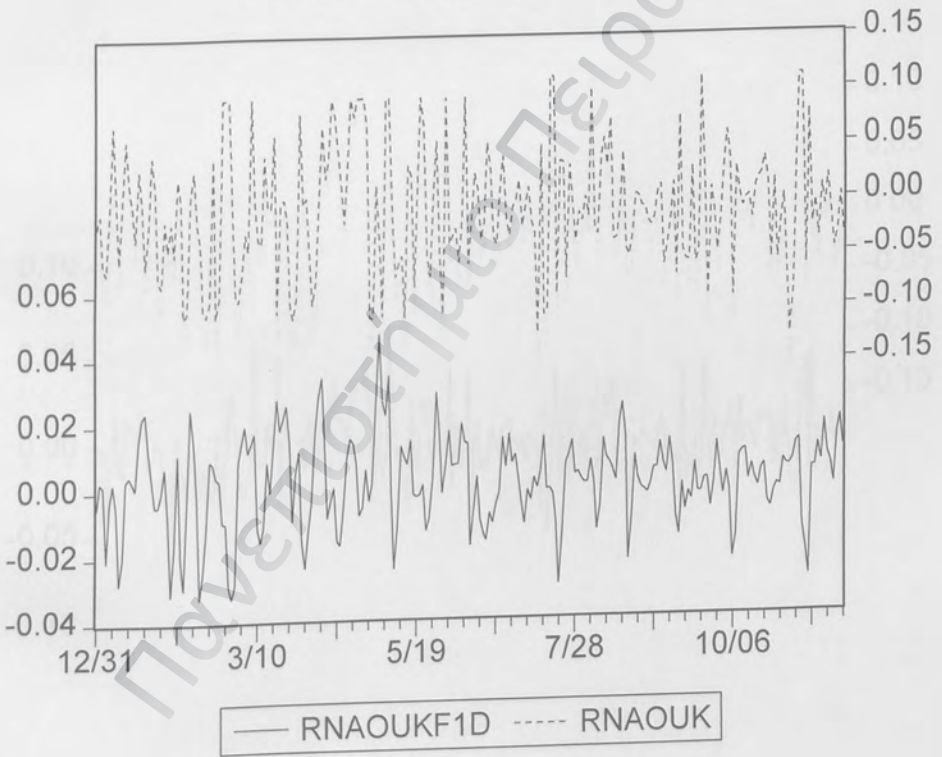
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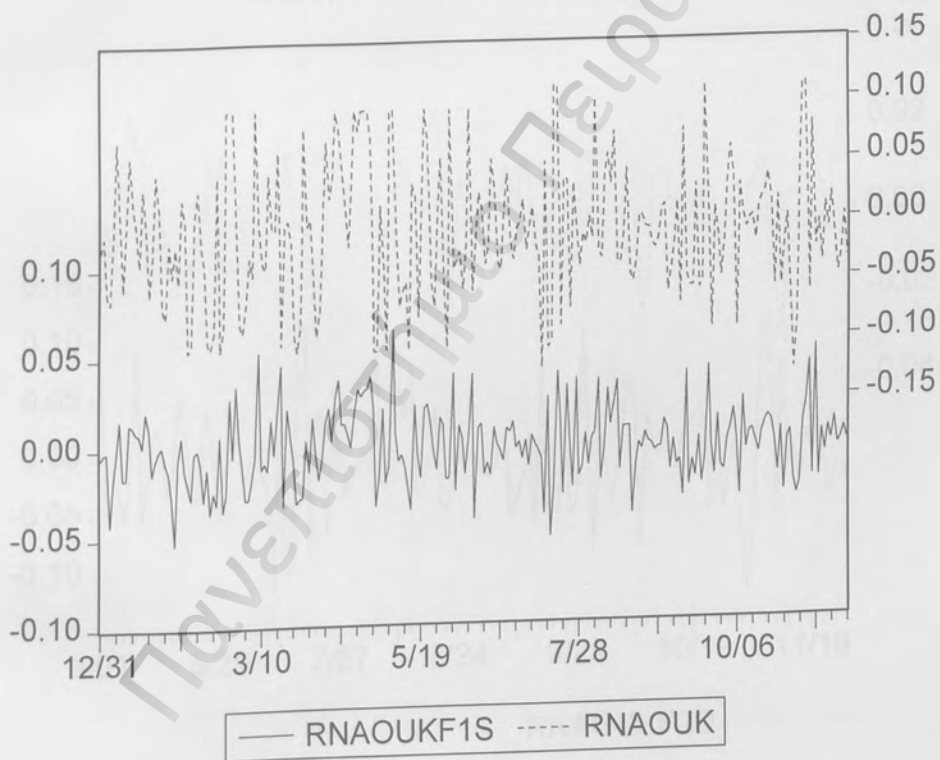
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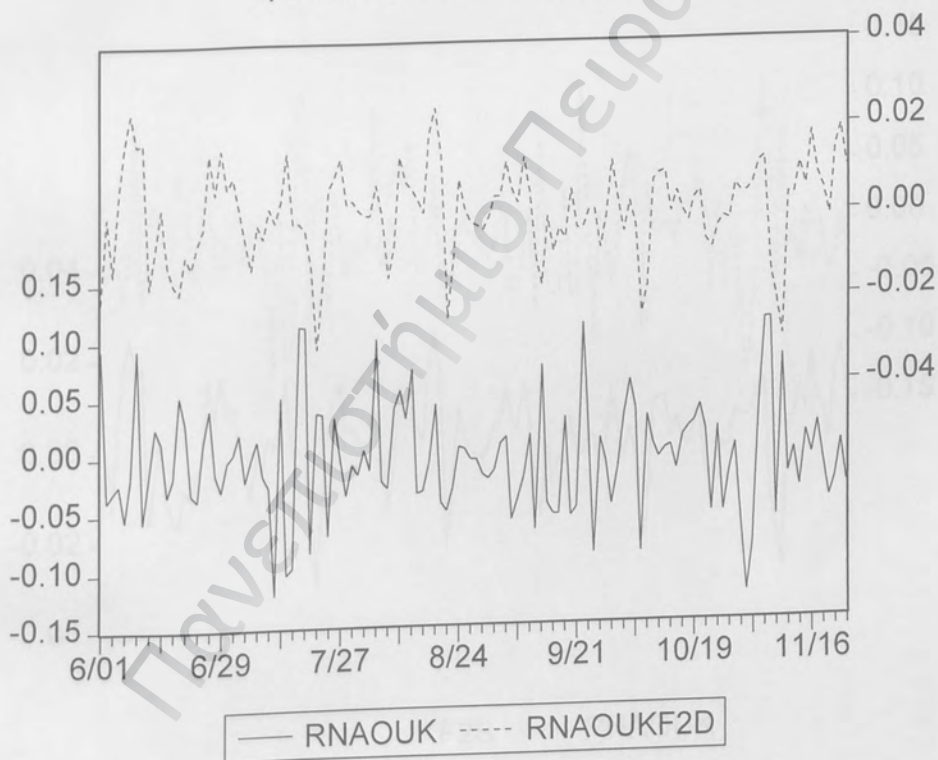
KLOSTIRIA NAOUSSIS
Real and forecasted series
Dynamic forecast from 19/1/2000



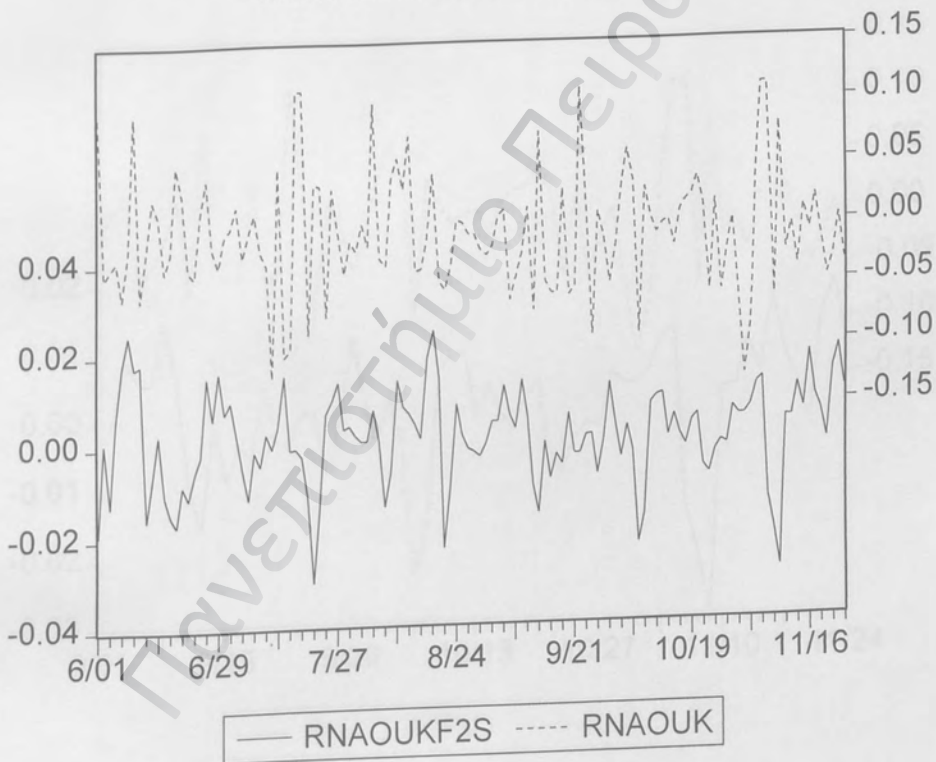
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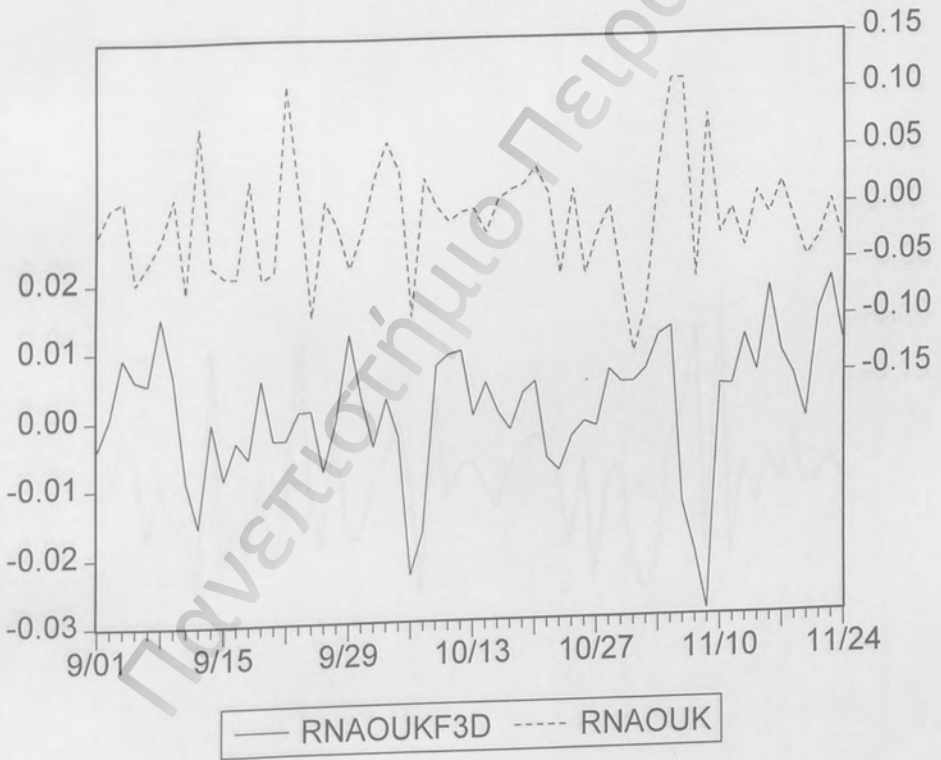
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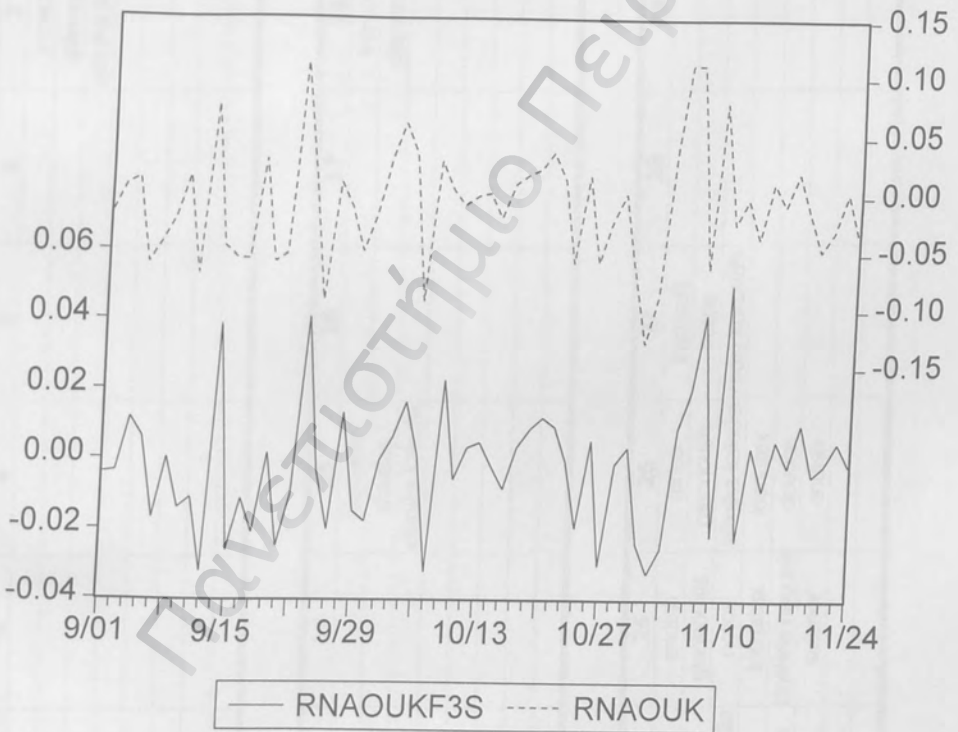
KLOSTIRIA NAOUSSIS
Real and forecasted series
Static forecast from 26/6/2000



KLOSTIRIA NAOUSSIS
Real and forecasted series
Dynamic forecast from 27/9/2000



KLOSTIRIA NAOUSSIS
Real and forecasted series
Static forecast from 27/9/2000



33	intralot	34	intracom Klonatex	35		36		37		38	intralot	39	klostiria naousis sidenor ellinika kalodia intracom	40		41	notos doudos ellinika kalodia sidenor	42	klostiria naousis doudos

43		44	intracom	45		46		47		48	intralot	49	sidenor ellinika kalodia	50		51		52	

53		54	fanco giannousis ellinika kalodia	55	notos	56	intralot

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΛΟΠΟΝΝΗΣΟΥ

