TEMPORAL AGGREGATION EFFECTS ON THE CONSTRUCTION OF PORTFOLIOS OF STOCKS OR MUTUAL FUNDS THROUGH OPTIMIZATION TECHNIQUES SOME EMPIRICAL AND MONTE CARLO RESULTS

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Abstract

In this paper we test the effects of temporal aggregation (disaggregation) on the efficiency of portfolio construction using the mean variance optimization approach. Using Monte Carlo techniques and empirical data from the Athens Stocks Exchange we confirm that the use of temporally aggregated data effects very seriously the efficiency of the constructed portfolio. Especially as the degree of temporal aggregation increases the application of optimization techniques could lead to different results regarding the percentage of stocks participation, the weights and finally the total portfolio performance.

Keywords: Portfolio Optimization, Stocks; Temporal Aggregation; Stochastic Simulation, The Banking Sector of the Athens Stocks Exchange;
JEL classification: C32, C43, C51, G14.

1. Introduction

Temporal aggregation poses many interesting questions which have been explored in time series analysis and which yet remain to be explored. An early example of research in this area is Quenouille (1957), where the temporal aggregation of $ARMA(p,d,q)$ processes is studied. Amemiya and Wu (1972), and Brewer (1973) review and generalize Quenouille's result by including exogenous variables. Zellner and Montmarquette (1971) discuss the effects of temporal aggregation on estimation and testing. Engle (1969) and Wei (1990) analyze the effects of temporal aggregation on parameter estimation in a distributed lag model. Other contributions in this area include Tiao (1972), Stram and Wei (1986), Weiss (1984), Rossana R.J. and Seater, J.J.,(1995), Granger and Silkos (1995), Marcellino (1999), and finally Tommaso Di Fonzo(2003) to name but a few.

In this paper we investigate the effects of temporal aggregation on the application of the mean variance approach in portfolio management[1]. More specifically we investigate the effects of temporal aggregation of the returns of the stocks of the portfolio. on the portfolio's performance, as this performance can be approximated from: (a) the percentage of the number o stock is participate in the portfolio, (b) the structure of the portfolio and finally (c) the future portfolio performance.

Using empirical data from the Athens Stocks Exchange and stochastic simulation techniques we end up with the general conclusion that the efficient portfolio management is closely related with the level of temporal aggregation (disaggregation) of the returns of the portfolio's stocks. In other words , the use of the returns of the stocks we want to participate to the portfolio, in daily, weekly, monthly etc basis, could lead us to different results about the number of the stocks to participate to the portfolio, the structure of the portfolio and finally the portfolio's future performance for different time horizons. This article is organized as follows. In section 2 we present very briefly the mean variance portfolio management and in section 3 we present the temporal aggregation effects on a portfolio management of stocks of the Banking sector of the Athens Stocks Exchange Market. Section 4 introduces the design of the simulation procedure and section 5 provides the simulation results. The last section concludes.

2.Mean Variance Frontier

Suppose there are N > 1 stocks and that $\mu \in R^N$ is a vector with the expected returns:

[1] Elton Edwin & Gruber Martin., (1977), Grinblatt M., Titman S., (1989) and Doumpos, M. and Zopounidis, C., (2002).

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ . \\ . \\ . \\ . \\ \mu_N \end{bmatrix} \quad \textbf{(1)}$$

Where $\mu_j \quad j = 1, 2, \ldots.., N$ refers to the j expected returns. Suppose Σ is a NxN variance – covariance matrix with the variance-covariance matrix of the expected returns of the $j = 1,2,..., N$ stocks.

$$\sum^{NxN} = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \cdots\cdots & \sigma_{1N} \\ \sigma_{21} & \sigma_2^2 \cdots\cdots & \sigma_{2\mathrm{N}} \\ \vdots & & \\ \vdots & & \\ \vdots & & \\ \vdots & & \\ \sigma_{\mathrm{N}1} & \sigma_{\mathrm{N}2} \cdots\cdots\cdots & .\sigma_{\mathrm{N}}^2 \end{bmatrix} = [\sigma_{ij}] \quad \textbf{(2)}$$

Where σ_{ij} corresponds to the covariance of the i and j stock (Mutual Fund). If the portfolio is a vector $w \in R^N$ with the constraint:

$$\sum_{j=1}^{N} w_j = 1 \quad \textbf{(3)}$$

Merton (1972) proved that a portfolio with weights w belongs to the mean variance frontier when: $w = g + hE$ for a level of expected returns E, when g and h are vectors of n dimensions and estimated as follows:

$$g = \frac{1}{D}\left[\mathrm{B}(\Sigma^{-1}\iota) - \mathrm{A}(\Sigma^{-1}\mu) \right] \quad \textbf{(4)}$$

$$h = \frac{1}{D}\left[C(\Sigma^{-1}\mu) - \mathrm{A}(\Sigma^{-1}\iota) \right] \quad (5)$$

Where A, B, C and D are constants defined as :

$$\mathrm{A} = i^{\mathrm{T}}\Sigma^{-1}\mu \quad \textbf{(6)}$$

$$\mathrm{B} = \mu^{\mathrm{T}}\Sigma^{-1}\mu \quad \textbf{(7)}$$

$$C = i^{\mathrm{T}}\Sigma^{-1}i \quad \textbf{(8)}$$

$$D = BC - A^2 \quad \textbf{(9)}$$

$$A, B, C, D \geq 0 \quad \textbf{(10)}$$

And with $\iota \in R^N$ a summation vector defined as :

$$i^T = \begin{bmatrix} 1 \\ 1 \\ \cdot \\ \cdot \\ \cdot \\ 1 \end{bmatrix} = \left[1\,1.......1 \right] \quad \textbf{(11)}$$

with Σ^{-1} is the inverse of the matrix Σ.

3.Temporal Aggregation Effects on the Portfolio of Bank Stocks

In order to study the effects of temporal aggregation we used daily data from the Athens Stock Exchange. The data cover the period 1995/1/1 – 2005/3/28.The data set concerns the returns of seven Banks of the Athens Stocks Exchange[2], namely[3]:

National Bank, General Bank, Eurobank, Emporiki Bank, Alfa Bank, Bank of Attika and the Bank of Greece. A graphical presentation of the diachronic behavior of these stocks (with basis the 3/1/1995) is given in Figure 1.

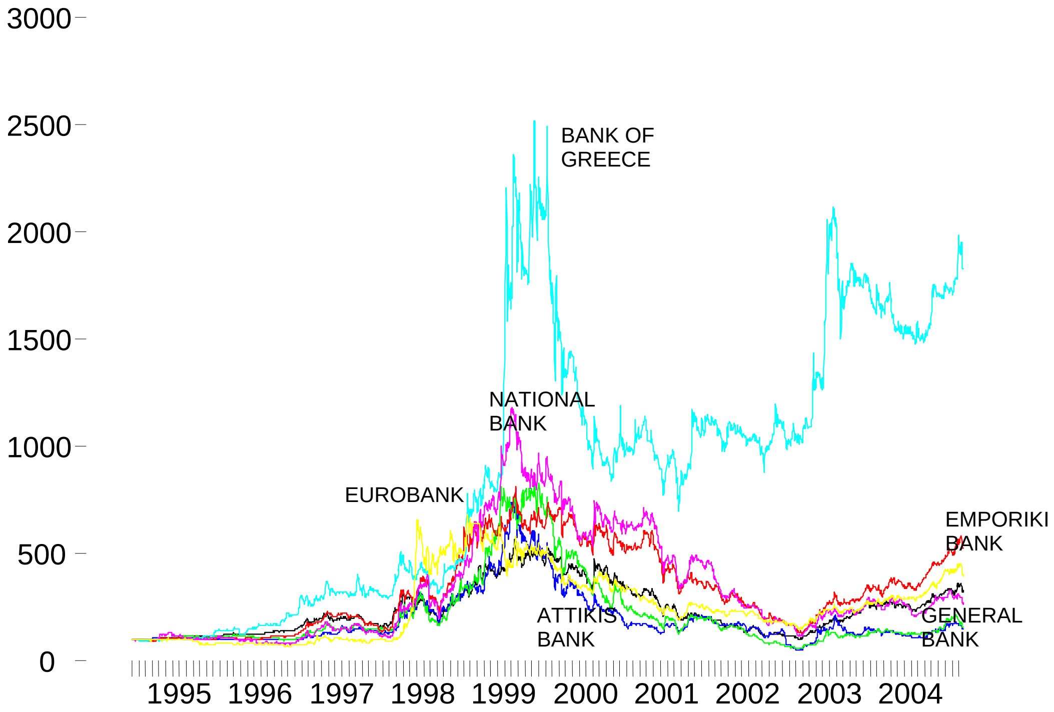

Figure 1: Competitive diachronic movement of the stock prices of the seven Banks of the Athens Stocks Exchange.

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[2] More about the characteristics of the Athens Stocks Exchange can be found in: Alexakis, P. and Petrakis, P., (1991),Apergis, N. and Eleptheriou, S., (2001), Barkoulas, J.T. and Travlos, N.G., (1998), Barkoulas, J.T., Baum, C.F. and Travlos, N.G., (2000), Bletsas, A. (1983), Coutts, J.A., Kaplanidis, C. and Roberts, J., 2000, Demos, A. and Parissi, S., 1998, Karathanassis, G. and Philippas, N., (1993), Karathanassis, G. and Philippas, N., (1993), Kirikos, D., (1996), Koutmos, G., Negakis, C. and Theodossiou, Laopodis, N. (1997), Mertzanis, H. and Siriopoulos, C., (1999), Milionis, A.E., Moschos, D., and Xanthakis, M., (1998), Milonas, N.T., (2000), Niarchos, N. and Alexakis, C., (1998) ,Papachristou, G., (1999), Papaioannou, G.J., Travlos, N.G. and Tsangarakis, N.V., (2000)

[3] We choose these stocks due to data availability reasons.

TABLE 1 Average Total Returns of the Portfolio at Different Management Periods using the Mean Variance Approach at 15 Different Levels of Temporal Aggregation.

Temporal Aggregation Level	100 Days Management Average Return %	100 Days Management Standard Deviation	200 Days Management Average Return %	200 Days Management Standard Deviation	300 Days Management Average Return %	300 Days Management Standard Deviation
1	-4,26989	0,248706	-1,73558	0,353866	-1,72507	0,441777
2	-3,76852	0,123603	-5,69069	0,180081	-4,81034	0,222945
3	-4,92971	0,03674	-6,99234	0,075287	-7,89973	0,110262
4	-3,6876	0,030984	-7,71721	0,033234	-9,27713	0,054897
5	-3,10115	0,023949	-6,18948	0,026599	-9,3336	0,028414
6	-1,61094	0,028352	-4,30539	0,028829	-7,02999	0,024573
7	-0,79912	0,032448	-2,19834	0,044801	-4,47001	0,043109
8	0,432031	0,030337	-0,58951	0,051161	-2,10361	0,05917
9	0,829176	0,027156	1,106782	0,045342	0,35224	0,062143
10	1,836383	0,031708	2,287912	0,044318	2,383864	0,062926
11	1,453018	0,025538	3,0804	0,03124	3,483179	0,044637
12	2,263866	0,021709	3,654791	0,025067	5,195121	0,036878
13	1,669787	0,017852	3,891006	0,019047	5,145972	0,023846
14	1,518146	0,018364	2,835893	0,016107	4,277454	0,017439
15	0,949198	0,017395	2,512184	0,017781	4,021305	0,02098

***Source*: Our Estimates**

On the Table 1 we present the results of applying the Markowitz[4] Mean Variance portfolio management on the seven stocks of the Banking Sector ,at 15 different levels of temporal aggregation, three portfolio management periods of 100, 200 and 300 days and for different dates of starting the portfolio management[5]. These average

[4] Markowitz, H. M. (1959).

[5] In order to make our results more representative the date of starting the portfolio management was selected randomly using 3000 experiments with random the starting day of the portfolio management. The mean returns refer to the 3000 experiments.

total returns are the means of the distributions of the 3000 iterations with random characteristic the date of starting the portfolio management. According to the results of Table 1 we observe a strong differentiation of our results regarding the average returns of the portfolio and the associated portfolio risk , at different levels of temporal aggregation(disaggregation). More specifically we observe an increase to the average total returns of the portfolio. Simultaneously we observe and a decrease to the average risk of the portfolio as the risk is measured from its standard deviation. Figures 2,3 and 4 presents the analogous distributions of average total returns at 15 different levels of temporal aggregation of a portfolio management with 100,200 and 300 days, respectively.

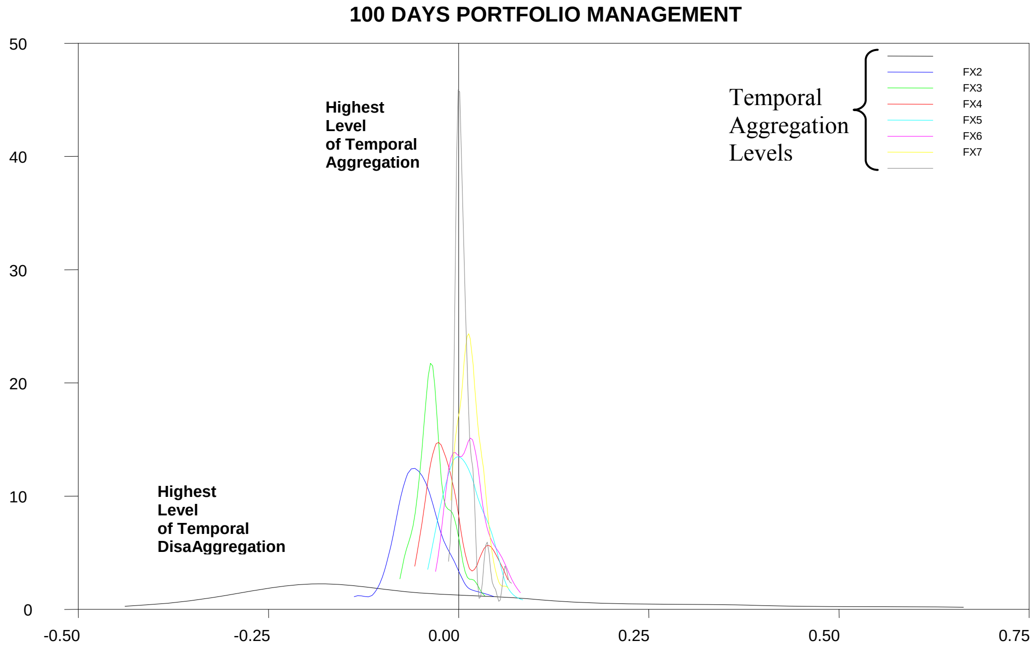

Figure 2. Average Returns Distributions at Different Levels of Temporal aggregation (100 Days Portfolio Management)

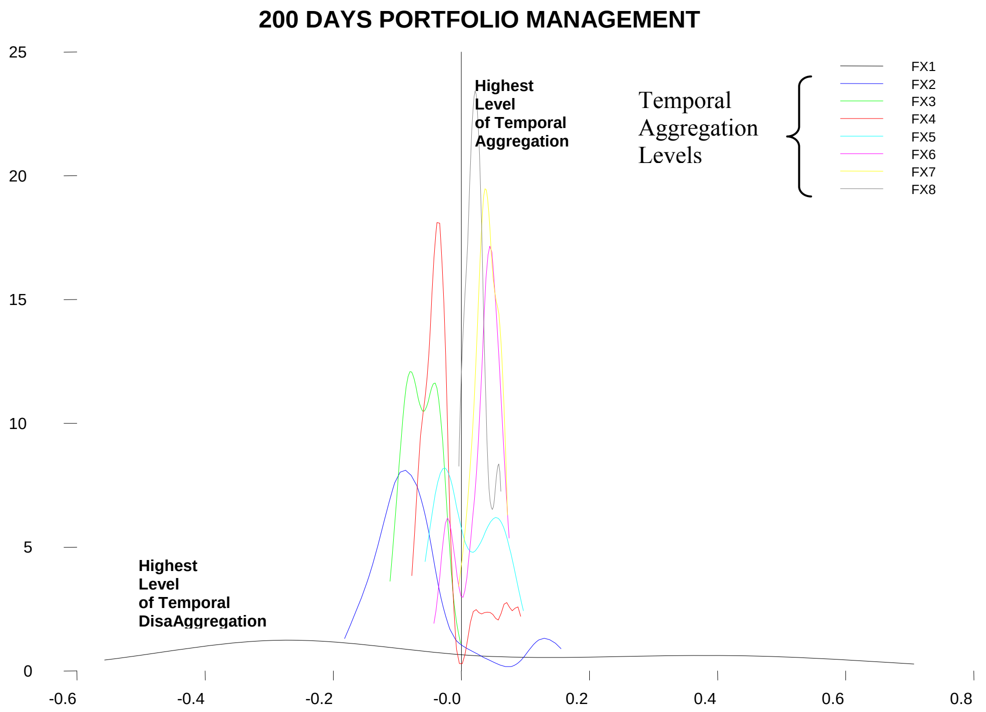

Figure 3. Average Returns Distributions at Different Levels of Temporal aggregation (200 Days Portfolio Management)

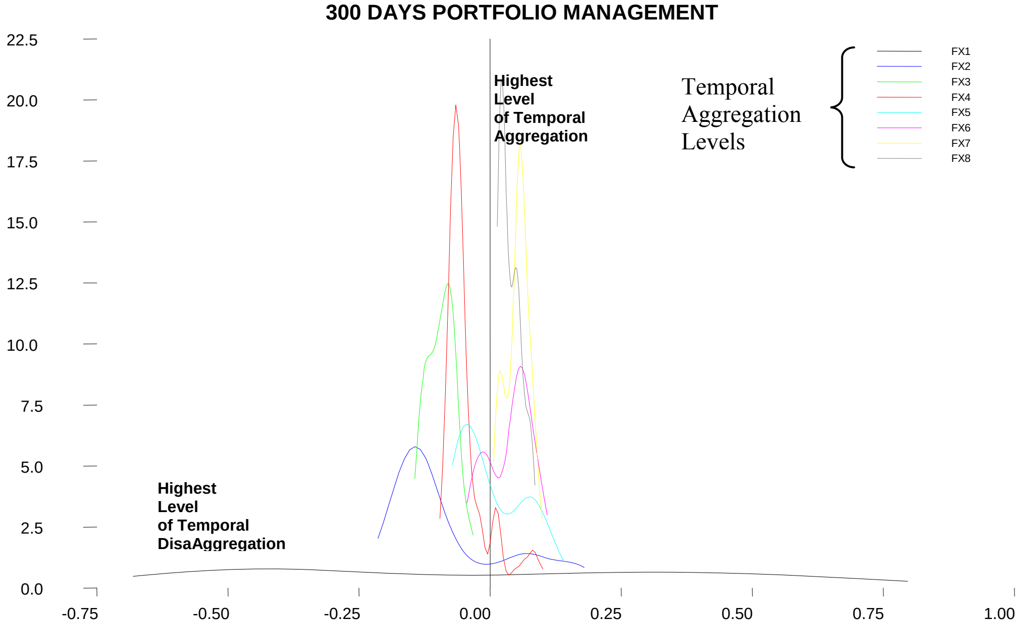

Figure 4. Average Returns Distributions at Different Levels of Temporal aggregation (300 Days Portfolio Management)

Finally in Figures 5 and 6 we present the average structure[6] of the portfolio of the seven stocks at different levels of temporal aggregation. It is obvious the differentiation of the average structure of the portfolio due the temporal aggregation effects.

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[6] If the structure w of the portfolio of the $j=1,2..,7$ stocks at a level of temporal aggregation A, on the $i=1,2,...,3000$ experiment is :

$$j=1,2,...,7$$

$w^A{}_{j,i}$ with $A=1,2,3,..,15$ then the average structure of the portfolio is defined as:

$$i=1,2,...,3000$$

$$mw_j{}^A = (\sum_{i=1}^{3000} w_{j,i}{}^A)/3000$$

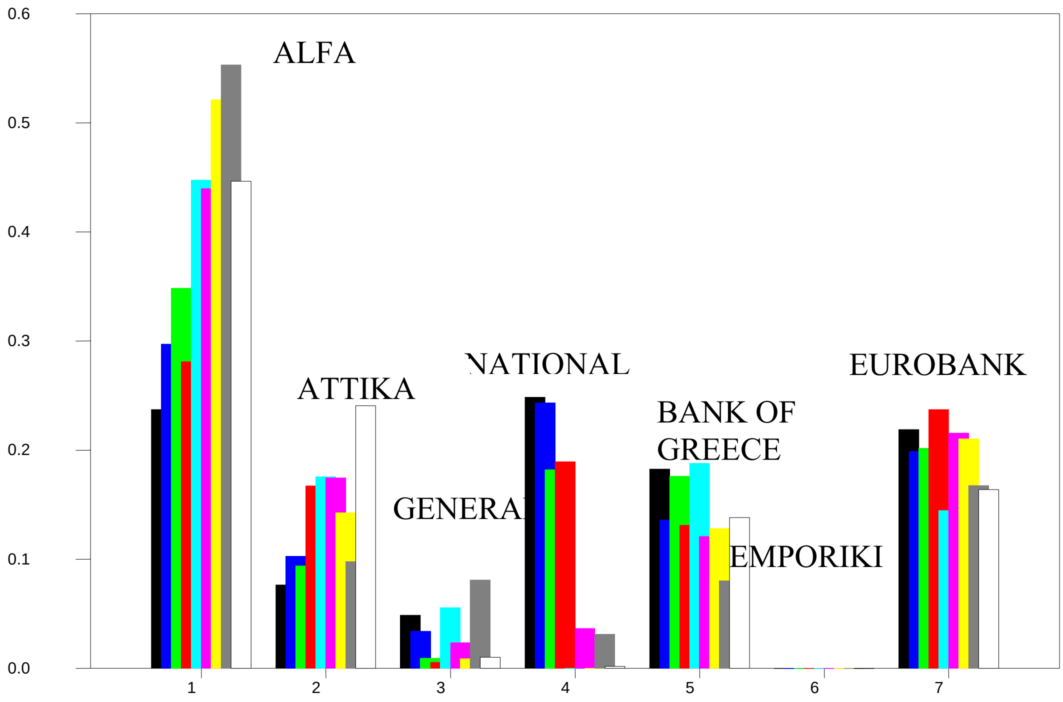

Figure 5. Average Structural of the Portfolio at Different Levels of Temporal Aggregation.

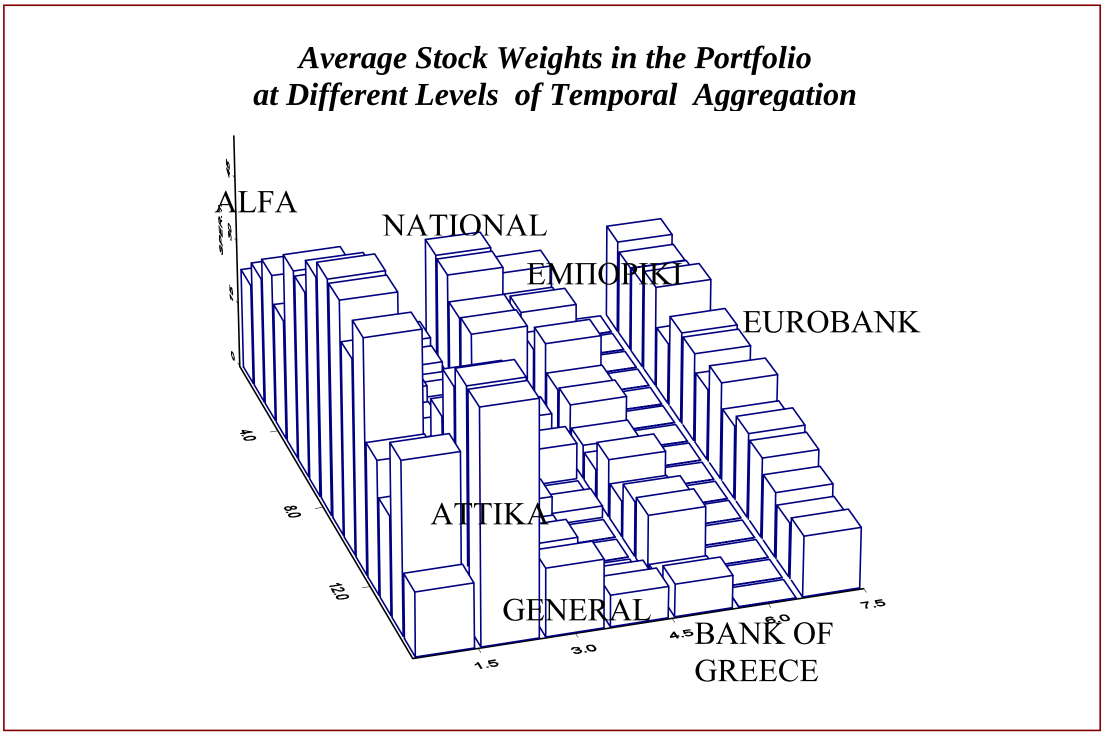

Figure 6. Average Structural of the Portfolio at Different Levels of Temporal Aggregation.

According to our empirical results the effects of temporal aggregation seems to be serious on the future returns of the portfolio, the structure and the number of the stocks to participate to the portfolio[7].

In the next section we use Monte Carlo experiments in order to generalize our results.

4.The Monte Carlo Experiments

In our simulation experiments we used two Data Generating Process(DGP). In the first process (A) we assume ARCH characteristics[8] and autoregressions[9] of the simulated returns:

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[7] More information about the participation number of the stocks to the portfolio structure is available on request.

[8] More sophisticated models were used in the simulation leading to similar results. More are available from the authors on request.

$$d_t = a_o + a_1 d_{t-1} + u_t \quad \textbf{(12)}$$

$$u_t = v_t \sqrt{(1 + 0.2 u_{t-1}^2)} \quad \textbf{(13)}$$

$$v_t \approx NID(0,1) \quad \textbf{(14)}$$

In the second process (B) we assume that the returns follow a pure random behavior with ARCH characteristics:

$$d_t = 0.027656 + u_t \quad \textbf{(15)}$$

$$u_t = v_t \sqrt{(1 + 0.2 u_{t-1}^2)} \quad \textbf{(16)}$$

$$v_t \approx NID(0,1) \quad \textbf{(17)}$$

where d_{jt} : the simulated returns of the j stock for $j = 1,2...,12$

u_t : disturbances with ARCH characteristics.

v_t :disturbances.

In our experiments we used 20 different level of temporal aggregation. For each temporal aggregation level we estimate the aggregate returns using the relation:

$$d_T{}^A = C^{k=j} d_t \quad \textbf{(18)}$$

Where $d_T{}^A$ is the time aggregated series, $j = 1,2,3,....,20$ refers to the time aggregation level and C is a time aggregation matrix of the form:

[9] In the simulations the parameters a_o *and* a_1 of (12) were specified as follows: $a_o = 0.06 \quad a_1 = Uniform\ Distribution(.2,.8)$

$$
C^j = (1/j)\begin{bmatrix}
\overbrace{11\ldots1}^{j} & 00\ldots0 & \ldots & 00\ldots0 & 00\ldots0 \\
00\ldots0 & \overbrace{11\ldots1}^{j} & \ldots & 00\ldots0 & 00\ldots0 \\
00\ldots0 & 00\ldots0 & \ldots & \overbrace{11\ldots1}^{j} & 00..0 \\
. & . & . & . & . \\
. & . & . & . & . \\
. & . & . & . & . \\
00\ldots0 & 00\ldots0 & \ldots & 00\ldots0 & \overbrace{11\ldots1}^{j}
\end{bmatrix} \quad \textbf{(19)}
$$

The following steps used in the application of the Monte Carlo experiment: Using the relations (12)-(14) και (15)-(18) we simulate the returns of the seven stocks at the highest level of temporal disaggregation. $(j = 1)$. We aggregate with the temporal aggregation matrix C^j with $j = 1,2,....20$ the returns $(d_{1t}, d_{2t},...., d_{12t})$ at the different temporal aggregation levels and apply the Markowitz approach. We repeat this procedure (NITERS=4000) 4000 times.

The ***Average total returns*** for the three period of portfolio management and the 20 temporal aggregation levels were estimated using the following relations:

Weights based on the mean variance management approach.

$$
w^A{}_{j,i} \quad \textbf{(20)}
$$

With: j = 1,2,..,NEQ (Number of stocks) , A=1,2,.,20 (Temporal aggregation Levels), i =1,2,,..NITERS (Number of iterations)

Portfolio Returns.

$$
r^A{}_{t,i=1,2...NITERS} = \sum_{j=1}^{NEQ} w^A{}_{j,i} d_{jt} \quad \textbf{(21)}
$$

$d_{1t}, d_{2t},...., d_{(NEQ)t}$: Simulated returns.

Total Returns

$$
{}^{Q}TR^A{}_{i=1,2,....NITERS} = \sum_{t=1}^{Q} \sum_{j=1}^{NEQ} w^A{}_{j,i} d_{jt} \quad \textbf{(22)}
$$

$Q = 100, 200, 300$ days, for the three periods of portfolio management.

Average Total Returns.

$$Mean\ \ Total\ \ \mathrm{Re}turns = (\sum_{t=1}^{Q} \ \sum_{j=1}^{NEQ} w^{A}{}_{j,i} d_{jt}) / NITERS \qquad \textbf{(23)}$$

The number of participants of the $j = 1,2,3,..,NEQ$ stocks in the portfolio for the NITERS is defined as follows:

$$N\_PARTICIP_j^A = N\_PARTICIP_j^A + 1, if\ w_j^A \neq 0 \qquad \textbf{(24)}$$

$$N\_PARTICIP_j^A = N\_PARTICIP_j^A + 0, if\ w_j^A = 0 \qquad \textbf{(24)}$$

for $j = 1,2,....,NEQ$ and $A = 1,2,...,20(Tempotal \quad Aggregation \quad Levels)$

The average portfolio structure is defined as follows:

$$mw_j{}^A = (\sum_{i=1}^{N\_PARTICIP^{A}{}_j} w_{j,i}{}^A) / N\_PARTICIP^{A}{}_j \qquad \textbf{(25)}$$

$j = 1,2,3,..,NEQ$

15. The Monte Carlo results

In this part of the paper we present the Monte Carlo results of the temporal aggregation(disaggregation) effects on the mean variance portfolio management approach. 4000 simulated observations (NITERS=4000) , for each of the 12 stocks simulated returns (NEQ=12) were obtained using the data generating process (A) and (B). In the portfolio management only 1600 observations were used to apply the mean variance approach and the whole number of iterations approaches the number 4000. In each of these iterations we applied the mean variance approach to obtain the number of the stocks and their optimal weights of the stocks of the portfolio at 20 different temporal aggregation levels. These stocks with their weights were then used for portfolio management with horizon of 100,200 and 300 days.

In Table 2 and in figures 7-9, we present the Mean Total Returns of three different portfolio management periods of 100,200 and 300 days, using the mean variance approach at 20 different temporal aggregation(disaggregation) levels using the data generating process (12)-(14). These results are similar with the analogous results of

Table 1 with regard the mean portfolio risk[10]. As temporal aggregation increases we observe an analogous decrease on the mean portfolio risk using actual and simulated data. What is more interesting is the average number of participation and the average weight of each stock in the portfolio. In the three dimensions figures 10 and 11 we present the behavior of the number of participation and the average weigh of each stock at different level of temporal aggregation(20 levels of temporal aggregation). As the temporal aggregation increase we observe a decrease in the number of the participations of the stocks in the portfolio with a simultaneous increase on the weigh with which each stock participates in the portfolio. The results of Table 3 are completely different compared with the previous case , indicating no serious effects of temporal aggregation on the portfolio management using the mean variance approach, in the case the stocks of the portfolio exhibits random characteristics.

TABLE 2. Mean Total Returns at different portfolio management periods applying the Markowitz Mean Variance Approach at 20 different levels of Temporal Aggregation based on the DGP: $d_t = a_o + a_1 d_{t-1} + u_t$, $u_t = v_t \sqrt{(1+0.2u_{t-1}^2)}$ and $v_t \approx NID(0,1)$ Number of stochastic simulations 4000

Temporal Aggregation Level	100 Days Management Average Return %	100 Days Management Standard Deviation	200 Days Management Average Return %	200 Days Management Standard Deviation	300 Days Management Average Return %	300 Days Management Standard Deviation
1	9,877491	4,404032	19,95309	6,449186	30,2264	9,877491
2	4,859673	2,187426	9,809902	3,172157	14,86547	4,859673
3	3,182101	1,444495	6,412295	2,095391	9,820026	3,182101
4	2,39523	1,088696	4,822328	1,572933	7,305912	2,39523
5	1,900838	0,873127	3,83324	1,260072	5,81606	1,900838
6	1,521763	0,718703	3,154493	1,045153	4,828034	1,521763
7	1,319368	0,618039	2,662349	0,894258	4,030283	1,319368
8	1,132461	0,542542	2,369774	0,793258	3,540171	1,132461
9	1,033757	0,497729	2,084912	0,710868	3,155198	1,033757

[10] The behavior of the mean total returns is not compatible as it depends on the characteristics of the actual stocks returns and the parameters of the simulated model.

TABLE 2 continues

Temporal Aggregation Level	100 Days Management Average Return %	100 Days Management Standard Deviation	200 Days Management Average Return %	200 Days Management Standard Deviation	300 Days Management Average Return %	300 Days Management Standard Deviation
10	0,938586	0,45213	1,891106	0,643665	2,863833	0,938586
11	0,845479	0,408212	1,696622	0,586485	2,564885	0,845479
12	0,747025	0,371393	1,508219	0,522958	2,373769	0,747025
13	0,654751	0,337094	1,407556	0,496214	2,178103	0,654751
14	0,657437	0,326758	1,318006	0,464761	1,986809	0,657437
15	0,55969	0,292005	1,218082	0,431829	1,885809	0,55969

***Source*: Our Estimates**

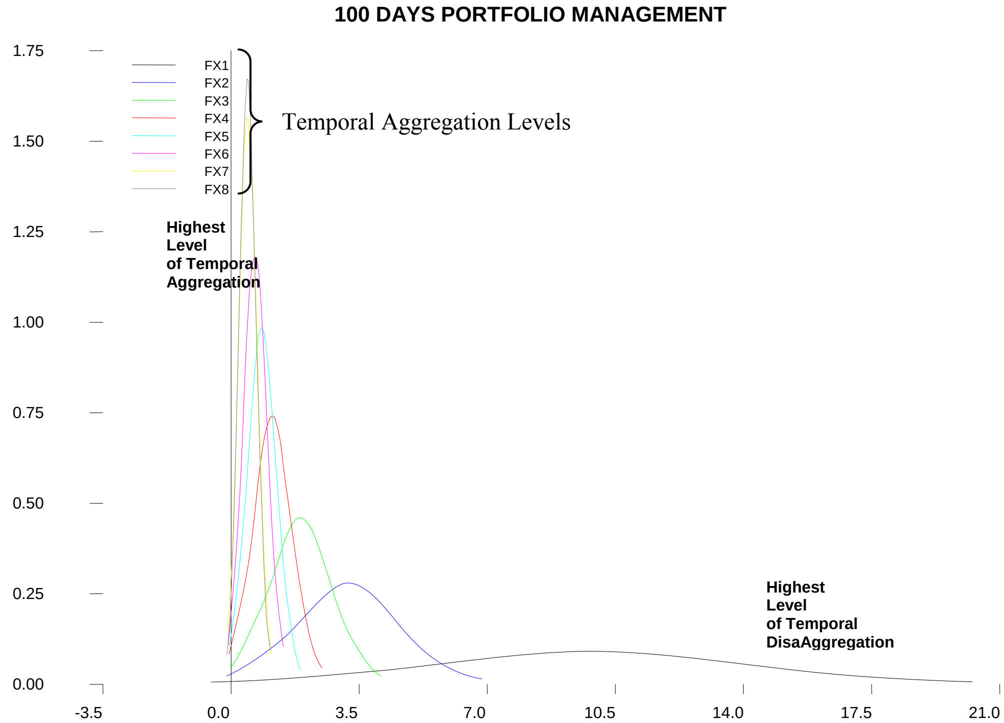

Figure7. Mean Returns Distributions at Different Levels of Temporal Aggregation (100 Days Portfolio Management)

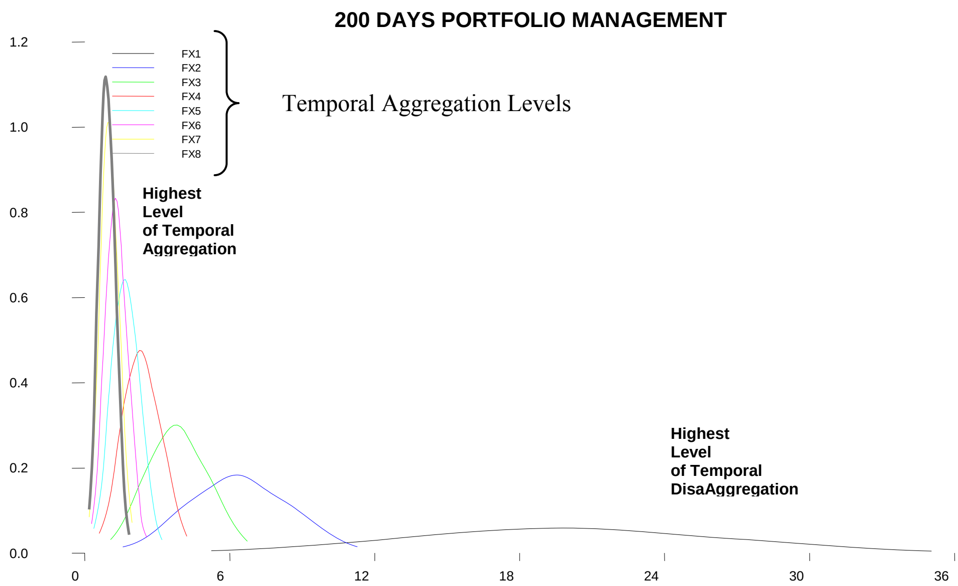

Figure 8. Mean Returns Distributions at Different Levels of Temporal Aggregation (200 Days Portfolio Management)

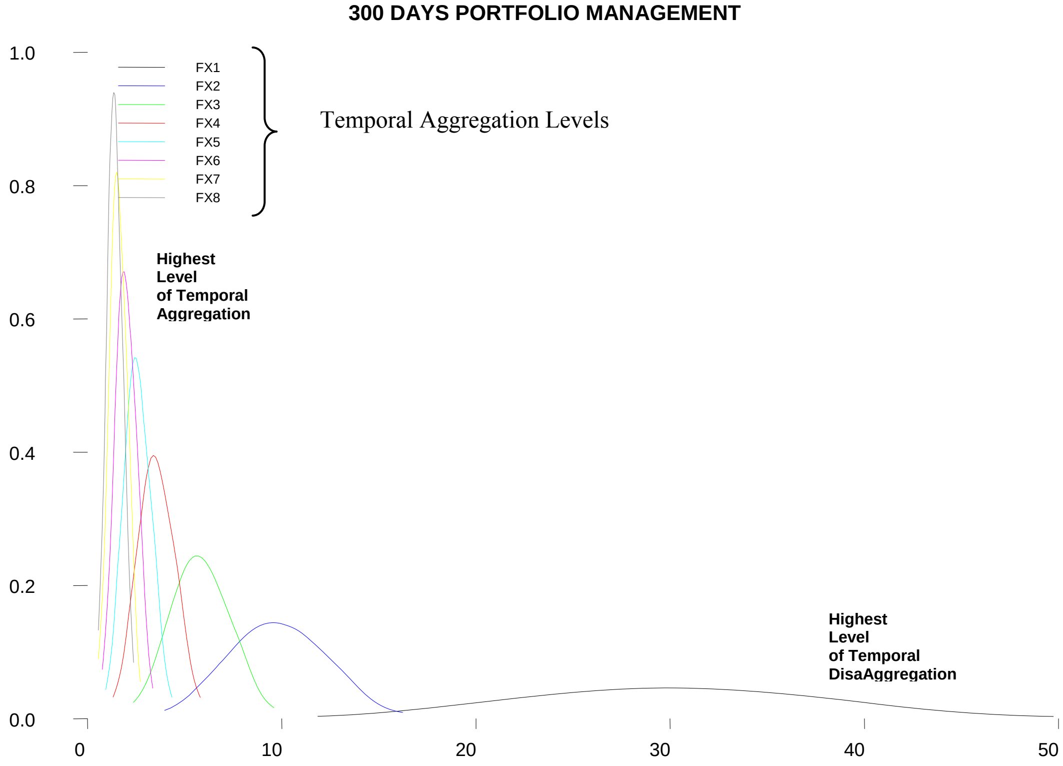

Figure 9. Mean Returns Distributions at Different Levels of Temporal Aggregation (300 Days Portfolio Management)

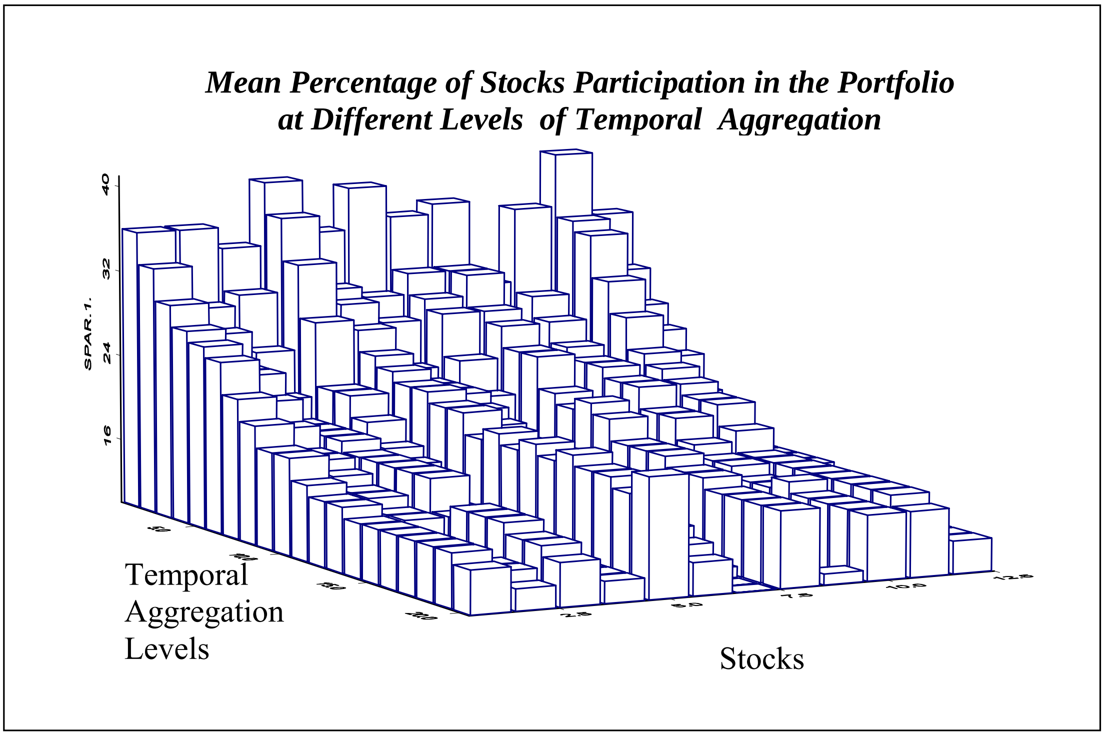

Figure 10. Percetage of participation of each stock in the portfolio at different level of temporal aggregation (Disaggregation).

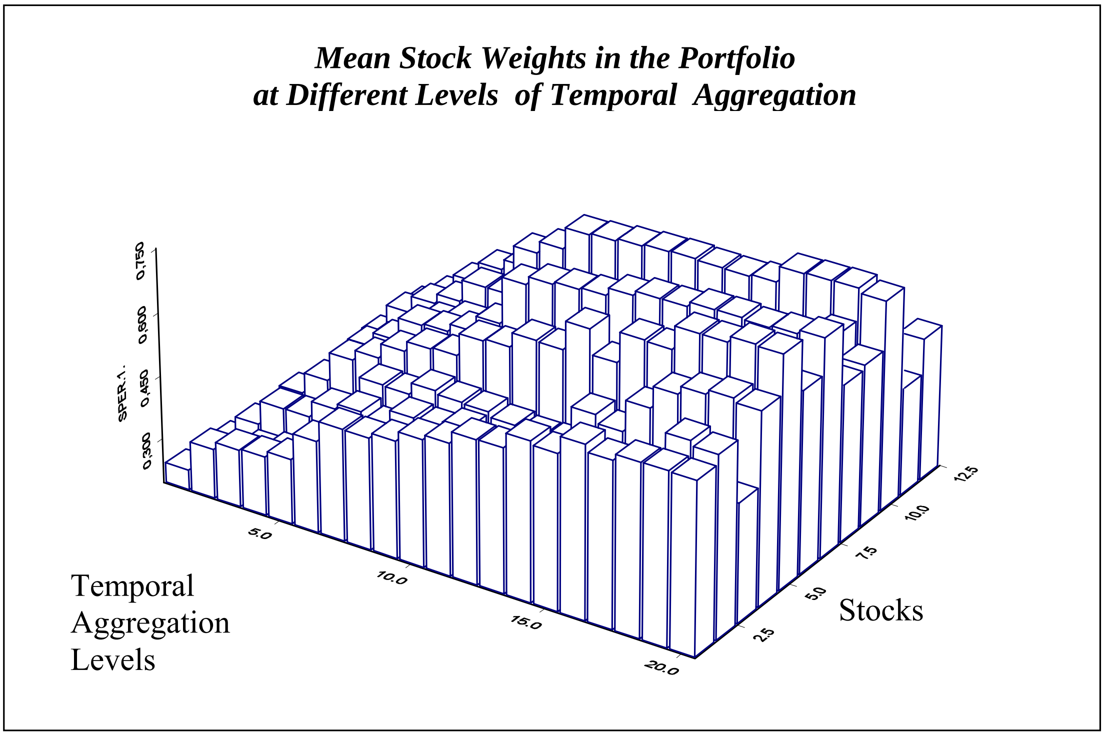

Figure 11. Mean Stock Weights at different level of temporal aggregation (Disaggregation).

TABLE 3. Average Total Returns at different Management periods applying the Markowitz Mean Variance at 20 different levels of Temporal Aggregation based on the DGP: $d_t = 0.027656 + u_t, u_t = v_t \sqrt{(1 + 0.2u_{t-1}^2)}$ and $v_t \approx NID(0,1)$ Number of stochastic simulations 4000

Temporal Aggregation Level	100 Days Management Average Return %	100 Days Management Standard Deviation	200 Days Management Average Return %	200 Days Management Standard Deviation	300 Days Management Average Return %	300 Days Management Standard Deviation
1	29,96946	1,411991	60,01385	1,963478	99,96048	2,538399
2	29,95714	1,55704	60,00749	2,173367	99,95497	2,769195
3	29,94403	1,725282	60,00138	2,400607	99,93769	3,034335
4	29,9456	1,878832	60,01538	2,616035	99,94721	3,283664
5	29,95962	2,031148	60,03782	2,837422	99,96961	3,544813
6	29,95003	2,177938	60,04175	3,041662	99,97051	3,808691
7	29,97418	2,29858	60,05984	3,216882	99,97872	4,029769
8	29,95898	2,419763	60,05824	3,375905	99,97938	4,228155
9	29,97588	2,533694	60,08823	3,582397	100,0244	4,477729
10	29,97907	2,646102	60,08217	3,714452	100,0341	4,651665
11	29,98784	2,734067	60,08085	3,848902	100,0187	4,819371
12	29,97169	2,831648	60,08964	3,999841	100,0228	4,958048
13	29,97793	2,908079	60,09445	4,113783	100,0389	5,124506
14	29,99946	2,9943	60,10229	4,240489	100,0362	5,320245
15	29,99261	3,08865	60,09851	4,369803	100,0487	5,487046
16	29,99401	3,148463	60,08641	4,466462	100,0515	5,605604
17	30,00599	3,228907	60,11446	4,600073	100,0555	5,74897
18	30,01007	3,318959	60,12062	4,727127	100,0468	5,948275
19	29,99432	3,394803	60,11317	4,798886	100,0434	6,017908
20	30,00813	3,466233	60,12032	4,925773	100,0412	6,22934

***Source*: Our Estimates**

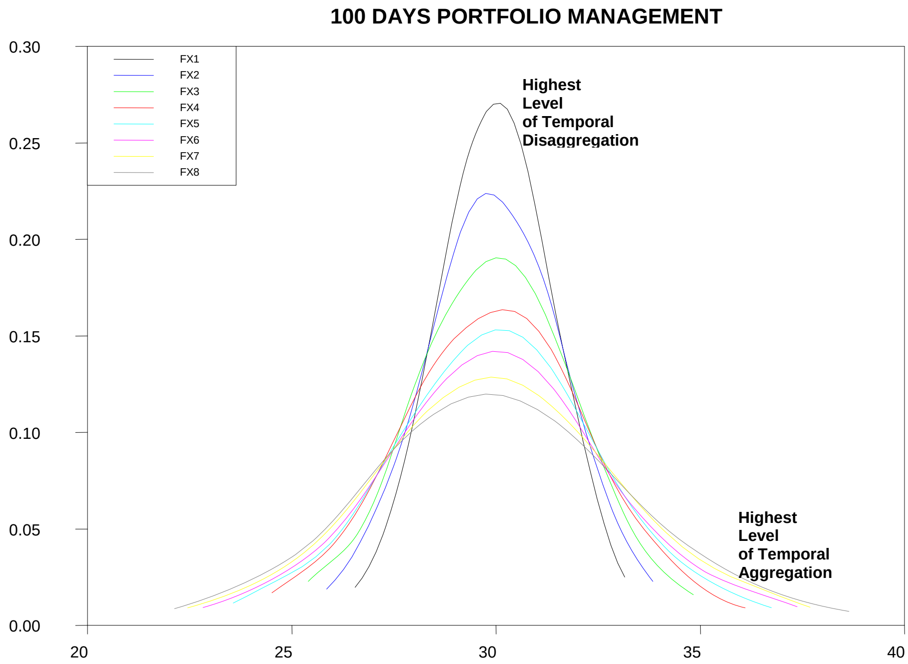

Figure 12. Average Returns Distributions at Different Levels of Temporal Aggregation (100 Days Portfolio Management)

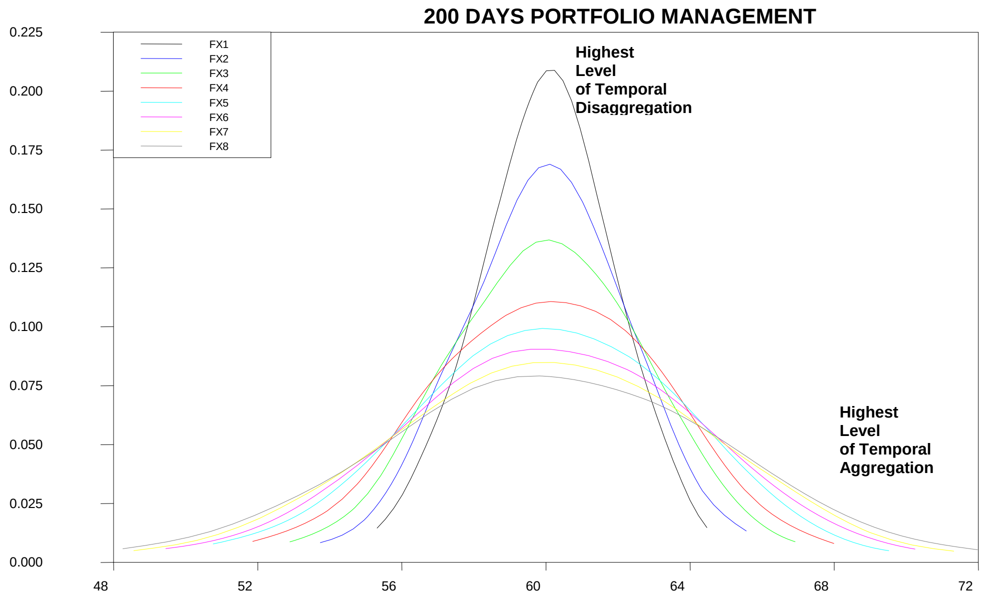

Figure13. Average Returns Distributions at Different Levels of Temporal Aggregation (200 Days Portfolio Management)

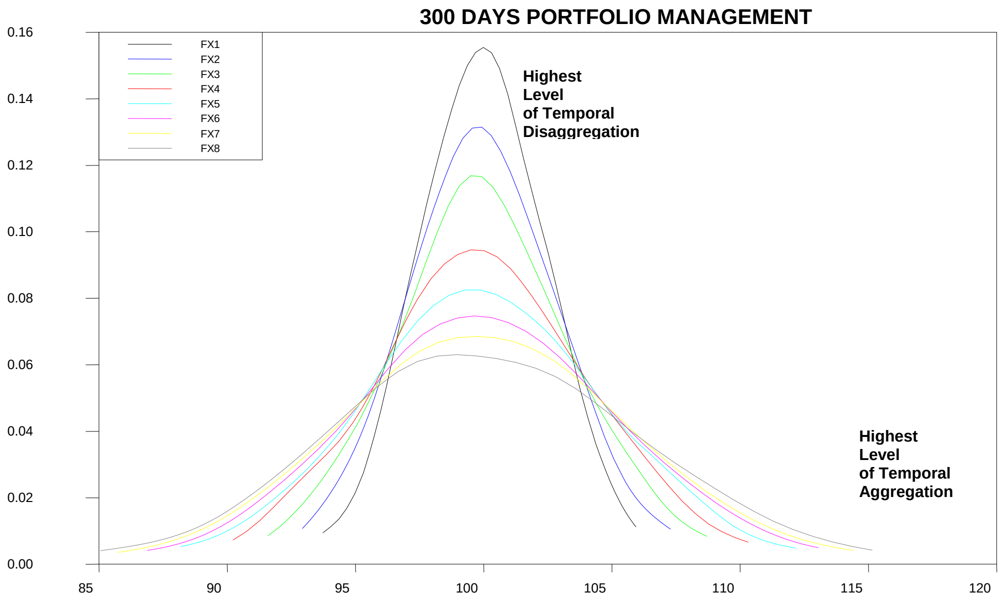

Figure14. Average Returns Distributions at Different Levels of Temporal Aggregation (300 Days Portfolio Management)

5. Conclusions

I this paper we analyze the effects of temporal aggregation on the efficient management of a portfolio of stocks using the Markowitz Mean Variance approach. Using real data of the Athens Stocks Exchange and simulation techniques we end up with the conclusions that efficient portfolio management is closely related with the appropriate level of temporal aggregation the returns are selected. The effects of temporal aggregation on the portfolio performance are very serious usually leading in different results related with the temporal aggregation level the data are used. The different results of temporal aggregation effects are related with the number each stock is participating in the portfolio, its weights in the portfolio and finally the future performance of the portfolio.

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