Temporal Aggregation and Systematic Sampling Effects on Non Linear Granger Causality Tests between Trade Volume and Returns.
Some Monte Carlo and Empirical Results from the Athens Stocks Exchange.

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Abstract.

Several tests for nonlinear causality are available on the literature. In this paper we investigate the effects of temporal aggregation and systematic sampling using some well known linear and nonlinear Granger causality tests. The conducted Monte Carlo simulation experiments and the empirical applications using data from the Athens Stocks Exchange Market, show that the use of temporally aggregated and systematic sampled data can affect seriously our conclusions about the linear or nonlinear causality effects between Trade Volume and Returns.

Keywords: Granger Non Linear Tests, Temporal Aggregation ,Systematic Sampling, Trade Volume and Returns.

JEL: C32,C43,C51

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I. INTRODUCTION

This paper addresses the question, how temporal aggregation affects structural inference and special linear and nonlinear Granger causality tests. Indeed this is an important issue, since in practice the frequency of observation is usually different from what may be called the 'natural' frequency of the underlying time series. For example, at financial markets, agents react very rapidly to news and, thus, the natural frequency of a model that describes the behavior of financial agents is likely to be minutes rather the hours or days. However, if the natural frequency of the underlying process is high relative to the observed frequency of the data, temporal aggregation and systematic sampling may completely change the structural relations in the system. It is therefore interesting to investigate the effects of temporal aggregation on structural inference and special in the case on nonlinear Granger causality.

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 ARIMA 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 (1978) analyze the effects of temporal aggregation on parameter estimation in a distributed lag model. Granger (1987) discusses the implications of aggregation on systems with common factors. Other contributions[1] in this area include Tiao (1972), Stram and Wei (1986), Weiss (1984), Granger and Lee (1999), and Marcellino (1999), to name but a few.

As is well known, it is preferable for developments concerning most economic magnitudes to be analyzed on the highest level of time disaggregation. Very often, however, the available data correspond to high levels of time aggregation, which frequently lead to erroneous results with respect to the diachronic interdependencies between the various economic variables. In fact, it is not uncommon to arrive at different results even when using the same magnitudes with

[1] The effects of time aggregation in univariate and multivariate time series work are explored by Tiao (1972), Brewer (1973), Shiller, R.J. and Perron, P. (1985), Oguchi and Furuchi (1990), Tserkezos (1993), (1998), (Drost and Nijman (1993), Pierce R and Snell A. (1995), Rossana and Seater (1995), C.W.J. Granger and P.L. Siklos,(1995), Gunningham S and Vilasuso (1995), Ng, S., 1995, Lahiri, K. and Mamingi, N., 1995. Choi, I. and Chung, B.S., (1995), Jesus Otero and Jeremy Smith., (2000) and Cook S. (2001).

different time aggregation.

Similar effects should also be expected in the case of the application of statistical methods to identify linear or nonlinear causality relations among economic magnitudes. Given the above, it is the aim of this paper to study the effects of temporal aggregation and systematic sampling on the efficiency of various linear and nonlinear Granger causality tests. More specifically, we report the results of a Monte Carlo experiment and an empirical application ,which examines the effects of time aggregation and systematic sampling on the effectiveness of the Hsiao's (1981) and the Peguin-Feissolle and Terasvirta (1999) linear and nonlinear causality tests respectively.

We found that as the time aggregation span widens, the likelihood of failing to determine the true effect of one variable to another approaches 95% for the case of nonlinear causality. Over a short aggregation span, the method of aggregation plays a crucial role. Over short aggregation spans, we found that systematic sampled aggregates over-perform two times in accepting the true hypothesis compared with the analogous temporal aggregation method. The results of this experiment support the use of systematic sampling data instead of data collected by temporal aggregated on a short time level.

Finally the results of this paper contribute to the empirical literature since for first time analysed the effects of temporal aggregation and systematic sampling in nonlinear causality tests.

This paper is organized as follows. Section 2 presents the standard Hsiao's (1981) linear test and a nonlinear Granger causality test suggested by Peguin-Feissolle and Terasvirta (1999). In Section 3 we presents our Monte Carlo experiment and the results of applying the above Granger causality tests. In Section 4 we present an empirical application testing nonlinear causality between trade volumes and returns of a Bank of the Athens Stocks Exchange and finally the last section concludes.

2. Testing Granger Causality.

2.1. Testing Linear Granger Causality.

To test series for linear causality Hsiao's (1981) linear causality test was used in our analysis. The test is based on a bivariate VAR representation for two stationary series x_t and y_t. Hsiao's sequential procedures for linear causality is based on the bivariate VAR representation

$$x_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j y_{t-j} + \varepsilon_{x,t} \tag{1}$$

$$y_t = \beta_0 + \sum_{i=1}^{n} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j y_{t-j} + \varepsilon_{y,t} \tag{2}$$

where x_t and y_t are stationary variables and n and q are the lag lengths of x_t and y_t respectively. The null hypothesis in the Granger causality test is that y_t does not cause x_t which represented by $H_0 : \beta_1 = \cdots \beta_q = 0,$ and the alternative hypothesis is $H_1 : \beta_i \neq 0$ for at least one j in Equation (1). The test statistic has a standard *F* distribution with (*n*, *T-n-q-1*) degrees of freedom, where T is the number of observations. Akaike Information Criterion is used to find the optimal lag lengths for both x_t and y_t.

Hsiao (1981) has suggested a sequential procedure for causality testing that combines Akaike's final predictive error criterion (FPE) and the definition of Granger causality. To test for causality from y_t to x_t ,the procedure consists of the following steps:

1. Treat x_t as a one-dimensional process as represented by Eq. (1) with βj = 0 ∀j, and compute its FPE with n varying from 1 to L, which is chosen arbitrarily. Choose the n that gives the smallest FPE, denoted FPE_x(n , 0).

2. Treat x as a controlled variable, with n as chosen in step 1 and y as a manipulated variable as in Eq. (1). Compute the FPE's of Eq. (1) by varying the order of lags of y_t from 1 to L and determine q , which gives true minimum FPE, denoted FPE_x(n , q).

3. Compare FPE_x(n, 0).) with FPE_x(n, q).If the former is greater than the latter, then it can be concluded that y_t causes x_t.

2.2. Testing for non-linear Granger causality

Hiemstra and Jones (1993) argue that the traditional Granger causality test, designed to detect linear causality, is ineffective in uncovering certain nonlinear causal relations and recommend the use of nonlinear causality test.

Baek and Brock (1992) have shown that available empirical evidences on the price-volume relationship based on linear Granger causality testing have low power against the nonlinear alternatives. Nonlinear dependence may be present if the price and volume are generated by nonlinear process.

According to Peguin-Feissolle and Terasvirta (1999), one important problem with the linear approach to causality testing is that such tests can have low power detecting certain kinds of nonlinear causal relations. Peguin-Feissolle and Terasvirta (1999) propose a statistical method for uncovering nonlinear causal relations that, by construction, cannot be detected by traditional linear causality tests. Their approach uses Taylor expansion series to detect the non-linearity.

The test is based on the idea of linearizing the unknown relationship they are not computationally more difficult to carry out than the linear test.

The test is based on a Taylor expansion of the nonlinear function:

$$y_t = f^*(y_{t-1}, \ldots, y_{t-q}, x_{t-1}, \ldots, x_{t-n}, \theta^*) + \varepsilon_t \qquad (3)$$

where θ^* is a parameter vector and $\varepsilon_t \sim nid(0,\sigma^2)$; the sequences $\{x_t\}$ and $\{y_t\}$ are weakly stationary and ergodic. The functional form of f^* is unknown but we assume that is adequately represents the causal relationship between x_t and y_t. It was also assumed that f^* has a convergent Taylor expansion at any arbitrary point of the sample space for every $\theta^* \in \Theta$.

In order to apply (3) to testing noncausality hypothesis, it is stated that x_t does not cause y_t if the past values of x_t does not contain any information about y_t that is already contained in the past values of y_t itself. More specifically, under the noncausality hypothesis,

$$y_t = f\left(y_{t-1},\ldots,y_{t-q},\theta\right)+\varepsilon_t. \tag{4}$$

To test (4) against (3), following Peguin-Feissolle and Terasvirta (1999), we linearize f^* in (3) by expanding the function into a *k*th-order Taylor series around an arbitrary fixed point in the sample space. After approximating f^*, merging terms and reparametrizing, we obtain:

$$\begin{aligned} y_t = {} & \beta_0 + \sum_{j=1}^{q}\beta_j y_{t-j} + \sum_{j=1}^{n}\gamma_j x_{t-j} + \sum_{j_1=1}^{q}\sum_{j_2=j_1}^{q}\beta_{j_1 j_2} y_{t-j_1} y_{t-j_2} + \sum_{j_1=1}^{q}\sum_{j_2=1}^{n}\delta_{j_1 j_2} y_{t-j_1} x_{t-j_2} \\ & + \sum_{j_1=1}^{n}\sum_{j_2=j_1}^{n}\gamma_{j_1 j_2} x_{t-j_1} x_{t-j_2} + \ldots + \sum_{j_1=1}^{q}\sum_{j_2=j_1}^{q}\cdots\sum_{j_k=j_k-1}^{q}\beta_{j_1\ldots j_k} y_{t-j_1}\ldots y_{t-j_k} \\ & + \ldots + \sum_{j_1=1}^{n}\sum_{j_2=j_1}^{n}\cdots\sum_{j_k-1}\gamma_{j_1\ldots j_k} x_{t-j_1}\ldots x_{t-j_k} + \varepsilon_t^* \end{aligned} \tag{5}$$

where $\varepsilon_t^* = \varepsilon_t + R_t^{(k)}(x,y)$, $R_t^{(k)}$ being the remainder, and $n \le k$ and $q \le k$ for notational convenience. Expansion (5) contains all possible combinations of lagged values of y_t and x_t up to order k. the assumption that x_t does not cause y_t means that all terms involving functions of elements of lagged values of x_t in (5) must have zero coefficients. Therefore, the null hypothesis of interest within (5) is:

$$H_{02}:\left\{\begin{array}{l}\gamma_j=0,\ j=1,\dots,n\\ \delta_{j_1 j_2}=0,\ j_1=1,\dots,q,\ j_2=1,\dots,n\\ \gamma_{j_1 j_2}=0,\ j_1=1,\dots,n,\ j_2=j_1,\dots,n\\ \vdots\\ \gamma_{j_1\dots j_k}=0,\ j_1=1,\dots,n,\ j_2=j_1,\dots,n,\dots,\ j_k=j_{k-1},\dots,n\end{array}\right\}$$

According to Pequin-Feissolle and Terasvirta (1999), there are two practical difficulties related to equation (5). One is numerical and the other one has to do with the amount of information. The numerical problem arises because the regressors in (5) tend to be highly collinear if both k, q and n are large. The other problem is that the number of regressors increases rapidly with k, so that the number of degrees of freedom may become rather small. A quick remedy suggested by Pequin-Feissolle and Terasvirta to both problems is the following. First divide the regressors in (5) into two groups: those being the function of lags of y_t only and the rest. Replace the regressors in (5) by the first p^* principal components of each matrix of observations. The null hypothesis is that the principal components of the latter group have zero coefficients. This yields the test statistic:

$$LM=\frac{(SSR_0-SSR_1)/p^*}{SSR_1/(T-1-2p^*}\qquad(6)$$

where SSR denoted sum of square residuals. The test has approximately an *F*-distribution with p^* and $T-1-2p^*$ degrees of freedom.

3. THE DESIGN OF THE MONTE CARLO SIMULATION.

The simulations are conducted using the following nonlinear stationary process:

$$y_t = 3.4 y_{t-1}(1 - y_{t-1}{}^2)e^{-y_{t-1}{}^2} + 0.5 y_{t-2} + 0.5 x^2{}_{t-1} + \varepsilon_{1t} \qquad (7)$$

$$x_t = 3.4 x_{t-1}(1 - x_{t-1}{}^2)e^{-x_{t-1}{}^2} + 0.8 x_{t-2} + \varepsilon_{2t} \qquad (8)$$

$$\varepsilon_{1t} \cong NID(0, \sigma_1{}^2)$$

$$\varepsilon_{2t} \cong NID(0, \sigma_2{}^2)$$

In the nonlinear system (7) and (8) , it is obvious that y_t is driven by x_t The nonlinearity[2] characteristics of both variables are given in Figures 1 and 2 respectively for y_t and x_t. The attractor reconstructed for the x_t time series is given in Figure 1 and the attractor of the time series y_t is given in Figure 2.

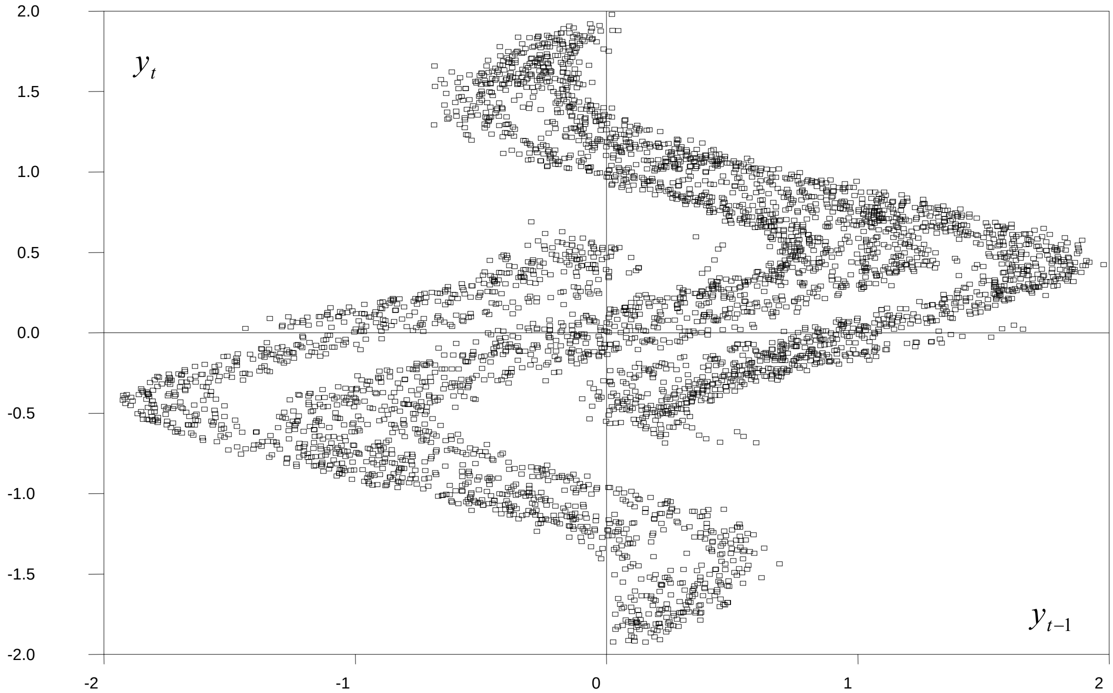

Figure 1. Constructed attractors from the y_t time series driven nonlinearly by y_{t-1}.

[2] Nonlinear dependence may be present if the two variables are generated by nonlinear processes.

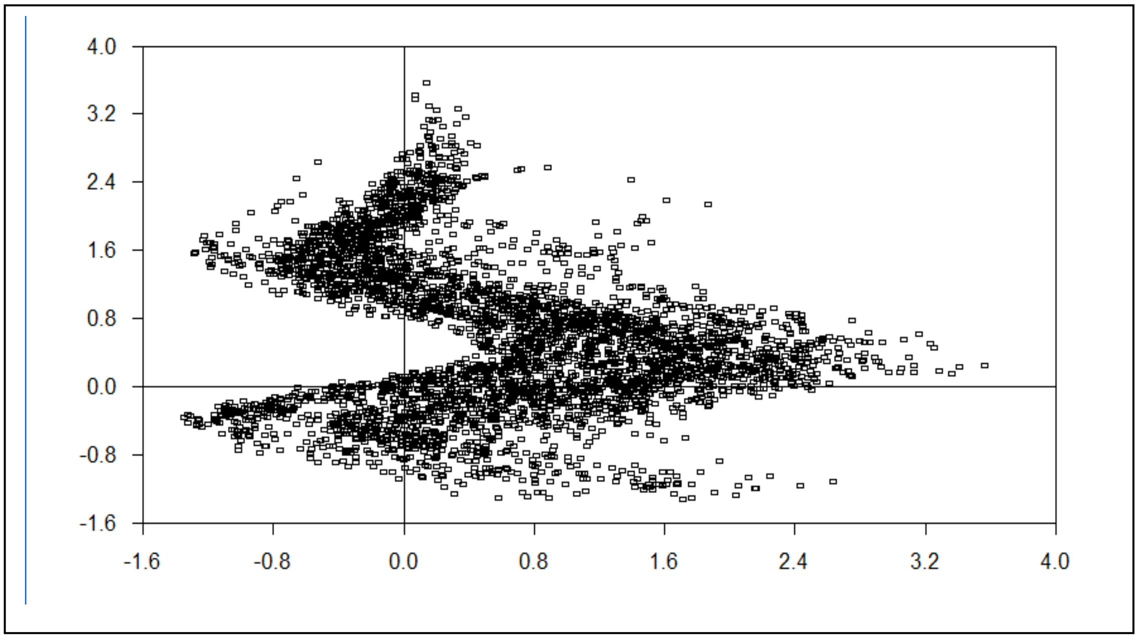

Figure 2. Constructed attractor from the x_t time series driven nonlinearly by x_{t-1}.

Impulse Responses.

Since the process (7) &(8) is a non linear one the impulse response of the variable x_t to y_t is time dependent and a simulation is presented in Figure 3 for different periods when the effect of x_t on y_t is taking place. The Average Diachronic Effect (Response Function) of the above process is given in Figure 4. This Average Impulse response has a duration of 130 periods.

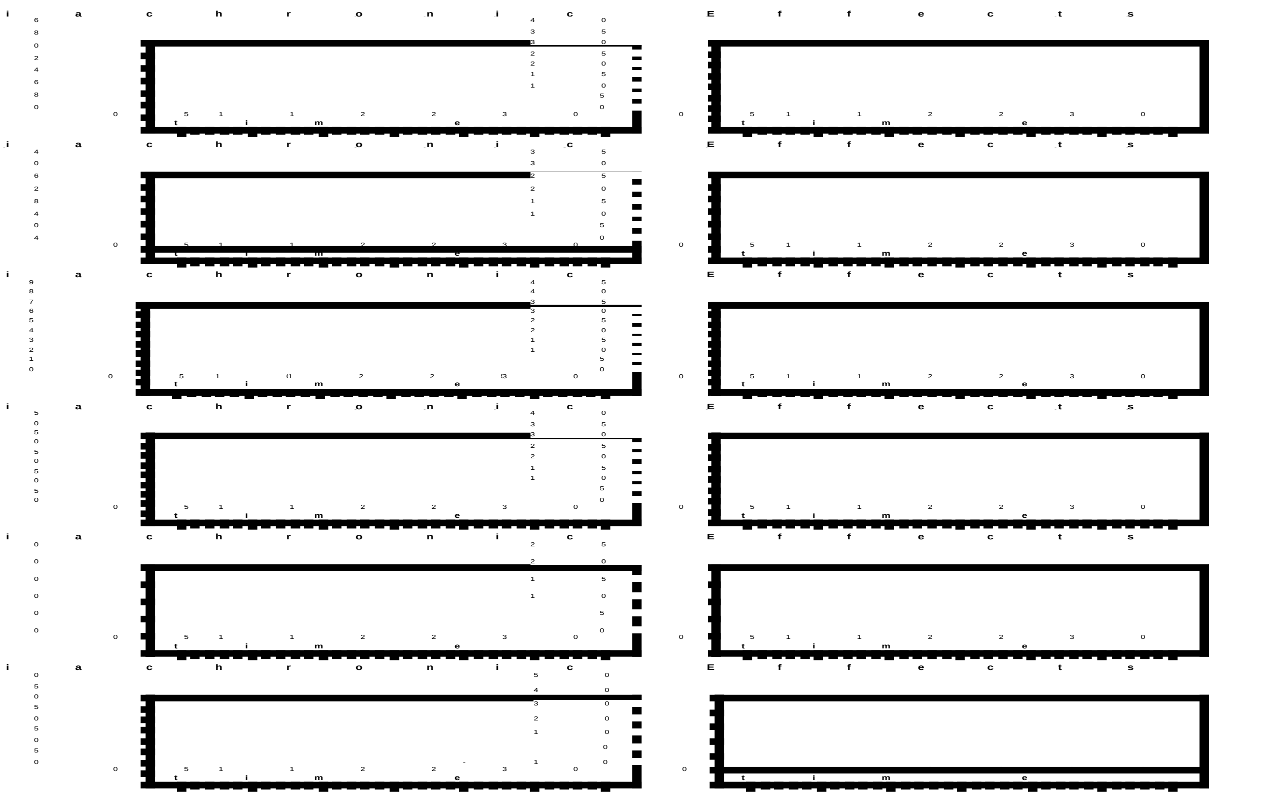

Figure 3.Simulated Impulse Responses of y to a change of x_t, at different time points in the estimation time interval.

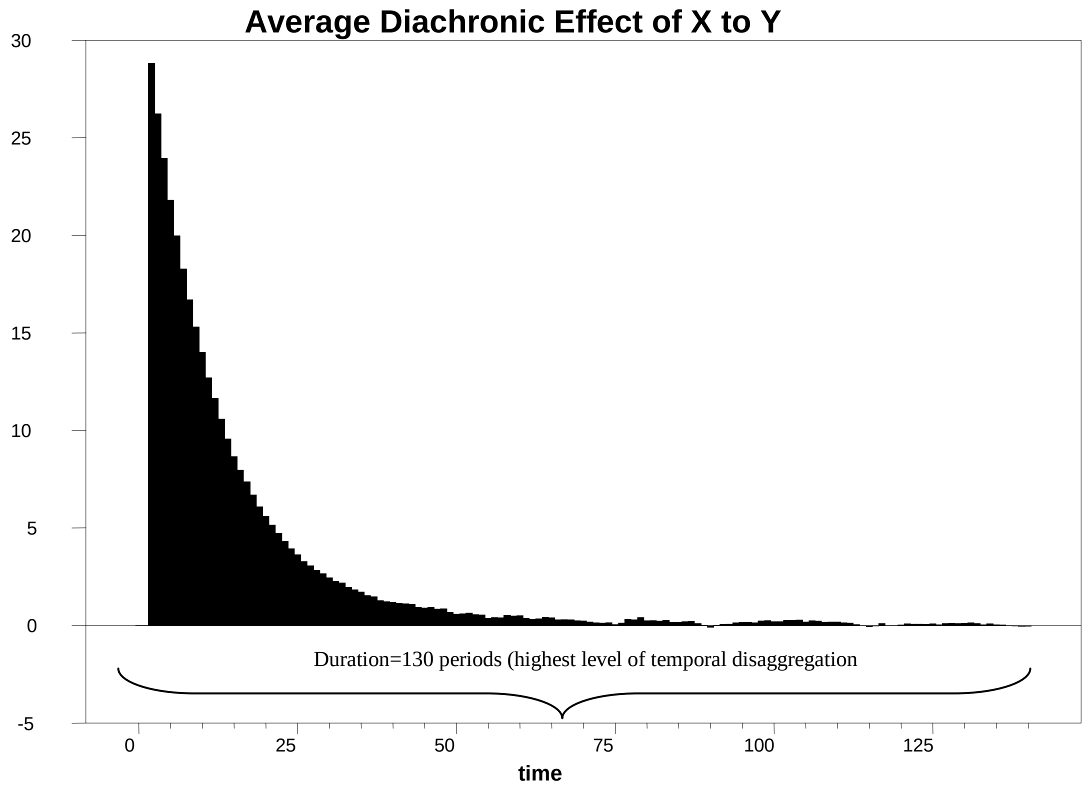

Figure 4. The 'Average' Impulse Response of x_t to y_t at the highest level of temporal aggregation.

In order to schematize the effects of temporal aggregation and systematic sampling on the ability of the Hsiao's procedure and the nonlinear granger causality test of Peguin-Feissolle and Terasvirta (1999) to identify any Granger type nonlinear causality in the variables of the process (7)-(8), we applied 20 different level of temporal aggregation. For each of the 20 different level of temporal aggregation we tested the causality of x_t to y_t using the above analyzed methods and the same time we estimated the impulse responses. The total number of the simulated observations was 1600 at the highest level of temporal disaggregation[3] and the experiment was replicated 4000 times.

[3] ***This gives us a total of 80 observations at the highest level of temporal aggregation.***

Consider first ***systematic sampling***. Systematic sampled data are constructed by resampling every m^{th} observation of the basic time series. Let $\hat{y}_t$ denote systematically sampled aggregates where T refers to the time unit of the aggregated data:

$$\hat{y}_t = y_{tm} \qquad (9)$$

Temporal aggregates , in contrast , are formed by averaging basic observations over nonoverlapping intervals. Let $y_T{}^A$ represent the temporally aggregated data:

$$y_T{}^A = Cy_t \qquad (10)$$

where $y_T{}^A$ is the temporal aggregated data , m is the time aggregation level and C is a time aggregation[4] matrix of the form :

$$C = \begin{bmatrix} 11...11000...........00000000000000 \\ 00000011....11000......0000000000 \\ 0000000000011....1100....000000 \\ .... \\ 0000...............0000000000111...11 \end{bmatrix} \qquad (11)$$

The steps of realization of the Monte Carlo experiments are the following:

- On the basis of the relations (7)-(8) in each iteration, we obtained 1600 simulated observations of the variables y_t and x_t
- For 20 different levels of time aggregation levels we tested the Probability of type I Error (Effects of x_t to y_t) for linear and nonlinear causality using the Hsiao's and the Pequin-Feissolle and Terasvirta (1999) approach respectively. Our results are presented on Table 1.
- Impulse responses comparisons were made after aggregating (for j=1,2,……,20) the simulated 'actual' responses at the analogous level of temporal aggregation (j^{th} level of

[4]***For more about these Time - Aggregation relations using matrix approach, see: Gilbert C., 1977., pp. 223-225. A similar aggregation formulation is*** $\overset{\approx}{r}_T = \frac{1}{m}(\sum_{j=o}^{m-1} L^j) r_t$ ***where L is the backshift operator on t.***

temporal aggregation) and the response on the estimated model and the j^{th} level of temporal aggregation. The criterion we used to do the comparisons was the :

Mean Square Error :

$$MSE_j = \sum_{i=1}^{Dur_j} (impul\_e^A{}_{ji} - impul\_e_{ji})^2 / Dur_j \qquad (12)$$

$$j = 1,2,....,20 \quad i = 1,2,3....,Dur_j$$

$$impul\_e^A{}_{ji} = C(impul\_e^s{}_{ji}) \qquad (13)$$

where:

$impul\_e^A{}_{ji} =$ Temporally Aggregated estimated impulse response at the j^{th} degree of temporal aggregation.

$impul\_e^s{}_{ji} =$ Simulated impulse response at the $j = 1$ degree of temporal aggregation.

$impul\_e_{ji} =$ Estimated impulse response at the j^{th} degree of temporal aggregation.

$Dur_j =$ Estimated Duration(length)[5] of the impulse response at the j^{th} level of temporal aggregation,

and C is the aggregation matrix (11)

[5] The estimation of the duration(length) of an impulse response is based on an loop which stops when the absolute impulse response is less than 0.000001 or the $(impul\_e_{ji} - impul\_e_{ji-1}) / impul\_e_{ji-1}) \leq 0.001$

Table 1. Probability of type I Error(Effects of x_t to y_t) at Different levels of Temporal Aggregation and Systematic Sampling.

	Temporal Aggregation				Systematic Sampling				
Temporal Aggregation Level	**Significance Level 0.025**	**Significance Level 0.05**	**Significance Level 0.1**	**Hsiao's Procedure**	**Systematic Sampling Level**	**Significance Level 0.025**	**Significance Level 0.05**	**Significance Level 0.1**	**Hsiao's Procedure**
1	58,2	64,5	71,0	56,6	1	58,2	64,5	71,0	56,6
2	25,0	33,0	42,1	55,0	2	78,7	83,8	88,7	46,3
3	30,1	37,7	48,1	42,1	3	69,1	75,6	82,0	47,8
4	19,4	26,8	37,1	49,8	4	56,7	64,4	73,1	44,3
5	22,5	30,1	39,6	39,3	5	45,1	52,9	63,4	44,3
6	15,3	21,9	32,4	46,3	6	34,2	42,8	53,1	44,7
7	16,5	23,2	32,7	39,9	7	26,0	33,5	44,5	40,2
8	12,8	18,6	27,2	43,9	8	20,9	27,8	38,3	43,3
9	10,9	17,3	26,4	39,8	9	17,6	23,9	33,2	39,8
10	10,6	15,6	23,2	42,7	10	13,1	19,7	29,1	35,3
11	8,6	13,9	22,8	38,4	11	11,5	17,1	25,2	36,3
12	7,7	13,1	21,3	40,5	12	10,5	15,2	22,7	35,2
13	8,1	12,3	19,1	38,4	13	8,5	13,4	20,9	34,0
14	6,6	10,5	18,5	37,3	14	7,4	11,8	18,9	35,1
15	6,2	10,4	17,0	37,3	15	6,2	10,5	16,9	31,6
16	5,2	9,3	16,7	37,2	16	6,7	10,5	15,8	31,5
17	5,2	8,9	15,2	34,4	17	5,6	9,2	16,4	33,0
18	4,6	8,2	14,4	36,6	18	5,4	8,8	15,1	32,7
19	4,6	8,5	15,1	37,0	19	4,7	7,8	14,2	33,0
20	4,3	7,2	13,7	35,5	20	5,2	8,6	14,6	34,4

Source: Our Estimates(Simulation Results).

Data entries are probabilities of accepting the true hypothesis ,i.e the existence of a causality from the variable x_t to the variable y_t. The tests were replicated 4000 times for the specification (7)-(8).The size of the tests is a=0.025,0.05 and 0.1 respectively. Data entries are given by $(n/4000)*100$ where n is the number of times the null is accepted.

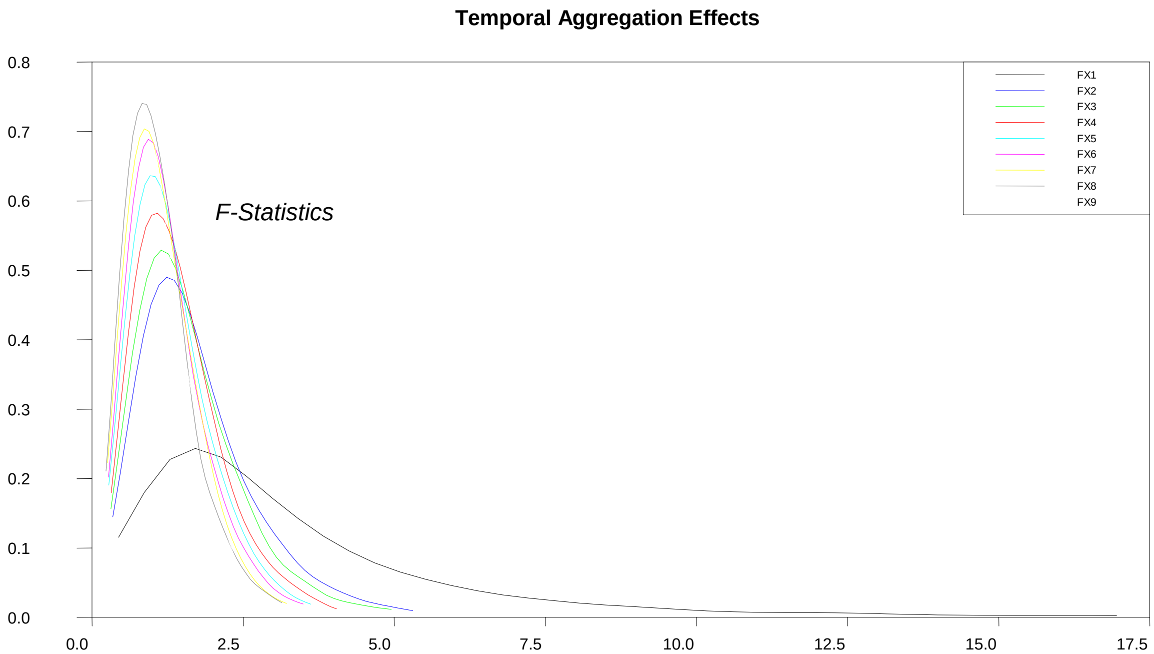

Figure 5. The distribution of F-statistic (11) at different levels of Temporal Aggregation.

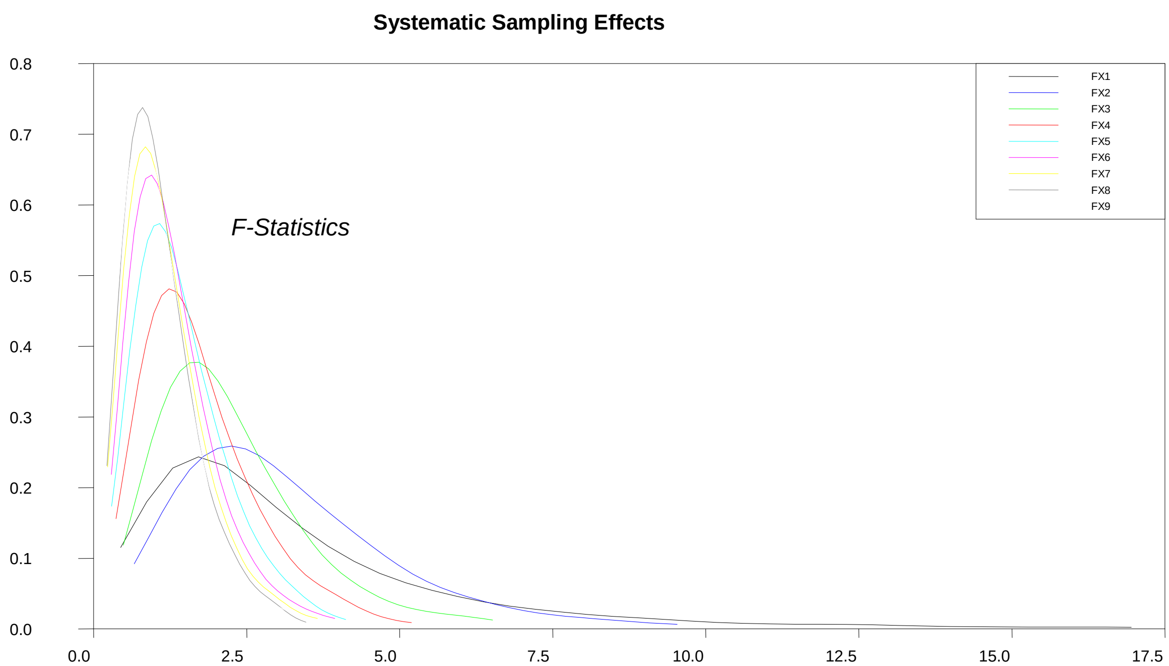

Figure 6. The distribution of F-statistic (11) at different levels of Systematic Sampling.

Table 2. Mean MSE between the estimated actual response at the j^{th} degree of temporal aggregation and the aggregated to the same temporal aggregation level of the actual(simulated) response.

Level of Aggregation	**Temporal Aggregation**	**Systematic Sampling**
1	0,410121	0,410121
2	1,411624	1,431902
3	2,473445	2,523624
4	3,694067	3,784691
5	5,098703	5,220104
6	6,761162	6,895104
7	8,331043	8,509493
8	10,15857	10,35502
9	11,83067	12,03199
10	13,58717	13,81476
11	15,5128	15,65688
12	17,45486	17,73481
13	19,59437	19,77152
14	21,05222	21,10672
15	23,20688	23,38979
16	24,61234	24,67157
17	26,85721	27,10557
18	28,18316	28,20312
19	29,29142	29,35723
20	30,46273	30,38935

Source: Our Estimates(Simulation Results).

The following conclusions regarding the applications of the two causality tests under different temporal aggregation and systematic sampling ,can be drawn from an analysis of the data in Table 1.

The percentages of successful detection of nonlinear causality is quite good and varies between 58,2%,64,46% and 70.96% for significance levels of 0.025,0.05 and 0.1 respectively.

As the temporal aggregation and systematic sampling increases the probability to accept the true hypothesis decreases for temporal aggregation and systematic sampling. At the highest level of temporal aggregation the probability of rejecting the true hypothesis is (100-4.3)% for temporal aggregation and (100-5.2)% for systematic sampling at a 0.025 significance level.(The analogous probabilities are (100-7.16)% for temporal aggregation and (100-8.6)% for significant level 0.05

and (100-7.3)% for temporal aggregation and (100-14.5)% for significant level 0.1 for temporal aggregation and systematic sampling respectively).

In the short time aggregation levels however the picture is the following: at a sampling interval of two to seven basic observations the probability to accept the true hypothesis using temporal aggregation is two times less than systematic sampling .These probabilities are on the average 40% and 20 % for systematic sampling and temporal aggregation respectively. Although the systematically sampled data typically out-perform their temporally aggregated counterparts over short period aggregation spans , they are similar over long aggregation spans.

Finally according our results on the diachronic effect of the variable x_t to the variable y_t we detect a serious increase in the Mean Square Error between the aggregated and the diachronic effect at the the j^{th} level of temporal of temporal aggregation. At the highest level of temporal disaggregation the MSE is 1.41 compared with a MSE of 30.4 at the highest level of temporal aggregation. Similar are the results for the case of systematic sampling effects. Finally in Figures 5 and 6 we present the distributions of the F-statistics at different levels of aggregation for the case of temporal aggregation and systematic sampling respectively.

4. Empirical Application.

In order to present the effects of temporal aggregation and systematic sampling on the efficiency on the nonlinear causality test of Peguin-Feissolle and Terasvirta (1999) we analyzed the diachronic relation[6] between returns and volume trade for the ALFA[7] Bank (Figure 7) of the Athens Stocks Exchange[8]. Daily data were obtained from the Athens Stocks Exchange Market and cover the period 1995:01:02 to 2005:03:22.

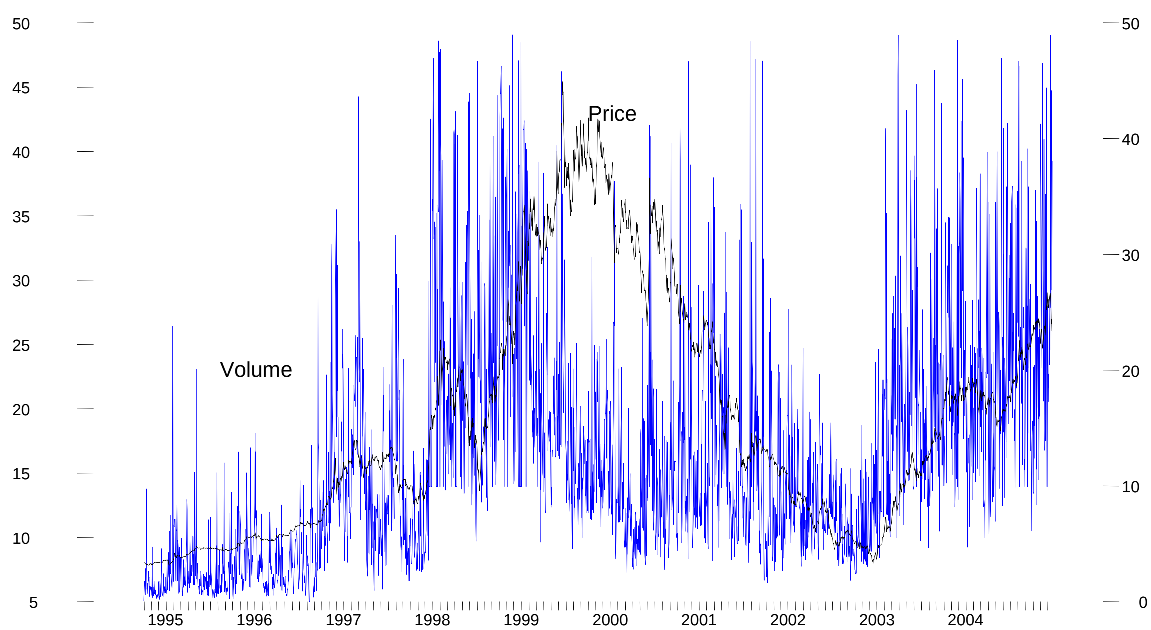

Figure 7. Trade Volumes and Stock Prices of the ALFA Bank.

On Table 3 and 4 we present the nonlinear causality effects between the Returns and the change of Traded Volumes of ALFA Bank at different significance levels, temporal

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[6] This relationship is important for a number of reasons. For example, Gallant et al. (1992) assert that more can be learned about the market by studying the joint dynamics of prices and trading volume than by focusing on the univariate dynamics of prices. Moreover, the trading volume is thought to reflect information about changes in investors' expectations. Another reason for the interest in the presence or otherwise of a strong price-volume relationship is that it provides support for using technical analysis as opposed (or in addition) to fundamental analysis.

[7] ALFA Bank is a leading Bank in the Athens Stocks Exchange Market.

[8] More results for the whole banking sector of the Athens Stocks Exchange are available by request from the authors.

aggregation and systematic sampling respectively[9]. From a careful inspection of these results we may conclude that the effects of temporal aggregation and systematic sampling in the efficient identification of possible non linear effects between these two variables is strongly related to the level of temporal aggregation and systematic sampling. Another interesting result (not presented here) is the disappearance of any linear granger causality between trade volumes and returns for the case of ALFA bank.

In Figures 3 and 4 we present the diachronic effects of the volumes to returns at different levels of temporal aggregation and systematic sampling respectively. There is an obvious differentiation in the duration and the shape of these effects at different temporal aggregation and systematic sampling level.

[9] More about the stationary tests and the isolation of the GARCH characteristics of the two series are available on request.

Table 3. NonLinear Causality Effects between Returns and Trade Volumes at Different Significance and Temporal Aggregation Levels for The case of ALFA Bank.

Effect of Returns to Trade Volumes					*Effect of Trade Volumes to Returns*				
Temporal Aggregation Level	**F-Statistic**	**Significance Level 0.025**	**Significance Level 0.05**	**Significance Level 0.1**	**Temporal Aggregation Level**	**F-Statistic**	**Significance Level 0.025**	**Significance Level 0.05**	**Significance Level 0.1**
1	2.55822	1.00000	1.00000	1.00000	1	1.95425	1.00000	1.00000	1.00000
2	2.47454	1.00000	1.00000	1.00000	2	2.48897	1.00000	1.00000	1.00000
3	2.49969	0.00000	0.00000	1.00000	3	1.38086	0.00000	0.00000	0.00000
4	2.92449	1.00000	1.00000	1.00000	4	1.64322	0.00000	1.00000	1.00000
5	0.97822	0.00000	0.00000	0.00000	5	1.00934	0.00000	0.00000	0.00000
6	0.82316	0.00000	0.00000	0.00000	6	1.65419	0.00000	0.00000	1.00000
7	2.25074	1.00000	1.00000	1.00000	7	2.38852	1.00000	1.00000	1.00000
8	2.46242	0.00000	1.00000	1.00000	8	0.93110	0.00000	0.00000	0.00000
9	0.19732	0.00000	0.00000	0.00000	9	0.73867	0.00000	0.00000	0.00000
10	3.41577	1.00000	1.00000	1.00000	10	1.00755	0.00000	0.00000	0.00000
11	1.41428	0.00000	0.00000	0.00000	11	1.90856	0.00000	1.00000	1.00000
12	2.40387	1.00000	1.00000	1.00000	12	3.82341	0.00000	1.00000	1.00000
13	1.88732	0.00000	1.00000	1.00000	13	9.12098	1.00000	1.00000	1.00000
14	1.52234	0.00000	0.00000	0.00000	14	0.86607	0.00000	0.00000	0.00000
15	0.37182	0.00000	0.00000	0.00000	15	2.65308	0.00000	0.00000	1.00000
16	3.13808	1.00000	1.00000	1.00000	16	1.76302	0.00000	0.00000	1.00000
17	2.33300	1.00000	1.00000	1.00000	17	0.18348	0.00000	0.00000	0.00000
18	4.13654	1.00000	1.00000	1.00000	18	2.39205	0.00000	0.00000	1.00000
19	2.60309	1.00000	1.00000	1.00000	19	1.20962	0.00000	0.00000	0.00000
20	3.14581	1.00000	1.00000	1.00000	20	1.48952	0.00000	0.00000	0.00000

Source: Our Estimates.

Symbol (1) corresponds to successful identification of a nonlinear Granger causality effect in contradiction to (0).

Table 4. NonLinear Causality Effects between Returns and Trade Volumes at Different Significance and Systematic Sampling Levels for The case of ALFA Bank.

Effect of Returns to Volumes					***Effect of Volumes to Returns***				
Systematic Sampling	**F-Statistic**	**Significance Level 0.025**	**Significance Level 0.05**	**Significance Level 0.1**	**Systematic Sampling**	**F-Statistic**	**Significance Level 0.025**	**Significance Level 0.05**	**Significance Level 0.1**
1	2.54707	1.00000	1.00000	1.00000	1	1.90758	1.00000	1.00000	1.00000
2	2.45078	1.00000	1.00000	1.00000	2	0.06843	0.00000	0.00000	0.00000
3	7.50322	1.00000	1.00000	1.00000	3	0.23346	0.00000	0.00000	0.00000
4	1.91978	0.00000	0.00000	0.00000	4	0.87544	0.00000	0.00000	0.00000
5	1.11291	0.00000	0.00000	0.00000	5	1.44437	0.00000	0.00000	0.00000
6	0.46501	0.00000	0.00000	0.00000	6	4.35180	1.00000	1.00000	1.00000
7	2.17579	0.00000	0.00000	0.00000	7	2.32212	1.00000	1.00000	1.00000
8	2.59272	0.00000	1.00000	1.00000	8	0.24721	0.00000	0.00000	0.00000
9	0.45451	0.00000	0.00000	0.00000	9	2.06533	0.00000	0.00000	0.00000
10	0.50326	0.00000	0.00000	0.00000	10	0.55781	0.00000	0.00000	0.00000
11	2.84661	0.00000	1.00000	1.00000	11	0.82744	0.00000	0.00000	0.00000
12	1.25773	0.00000	0.00000	0.00000	12	2.69147	0.00000	0.00000	1.00000
13	1.47857	0.00000	0.00000	0.00000	13	0.30865	0.00000	0.00000	0.00000
14	2.90983	1.00000	1.00000	1.00000	14	0.14289	0.00000	0.00000	0.00000
15	0.36589	0.00000	0.00000	0.00000	15	0.04198	0.00000	0.00000	0.00000
16	1.29395	0.00000	0.00000	0.00000	16	0.41181	0.00000	0.00000	0.00000
17	2.76751	1.00000	1.00000	1.00000	17	0.44785	0.00000	0.00000	0.00000
18	2.93878	0.00000	0.00000	1.00000	18	2.76222	0.00000	0.00000	1.00000
19	2.06083	0.00000	0.00000	1.00000	19	4.15927	1.00000	1.00000	1.00000
20	0.01179	0.00000	0.00000	0.00000	20	0.67848	0.00000	0.00000	0.00000

Source: Our Estimates.

Symbol (1) corresponds to successful identification of a nonlinear Granger causality effect in contradiction to (0).

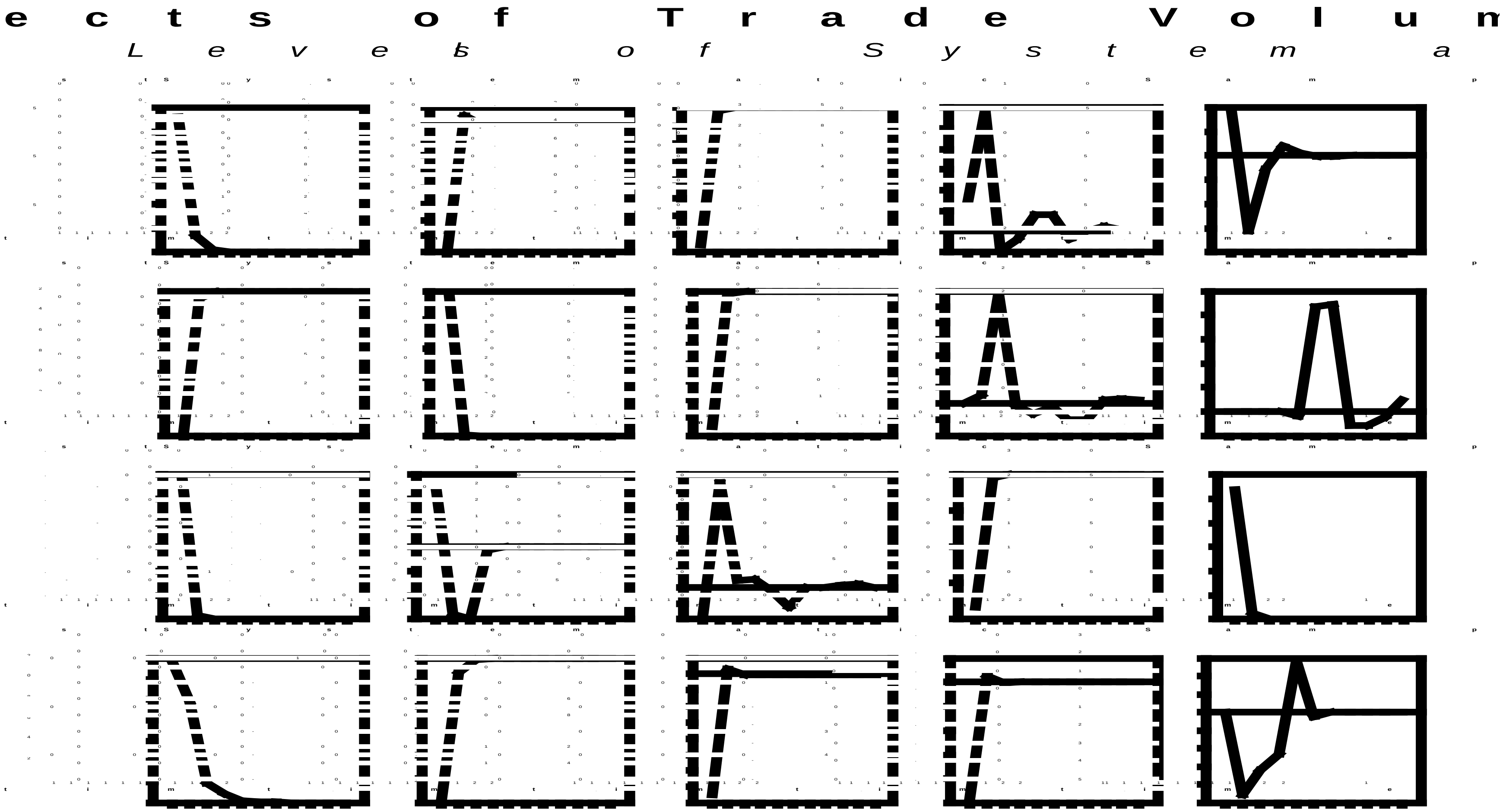

Figure 8. Diachronic effects of trade volumes to returns of ALFA Bank at different levels of Temporal Aggregation.

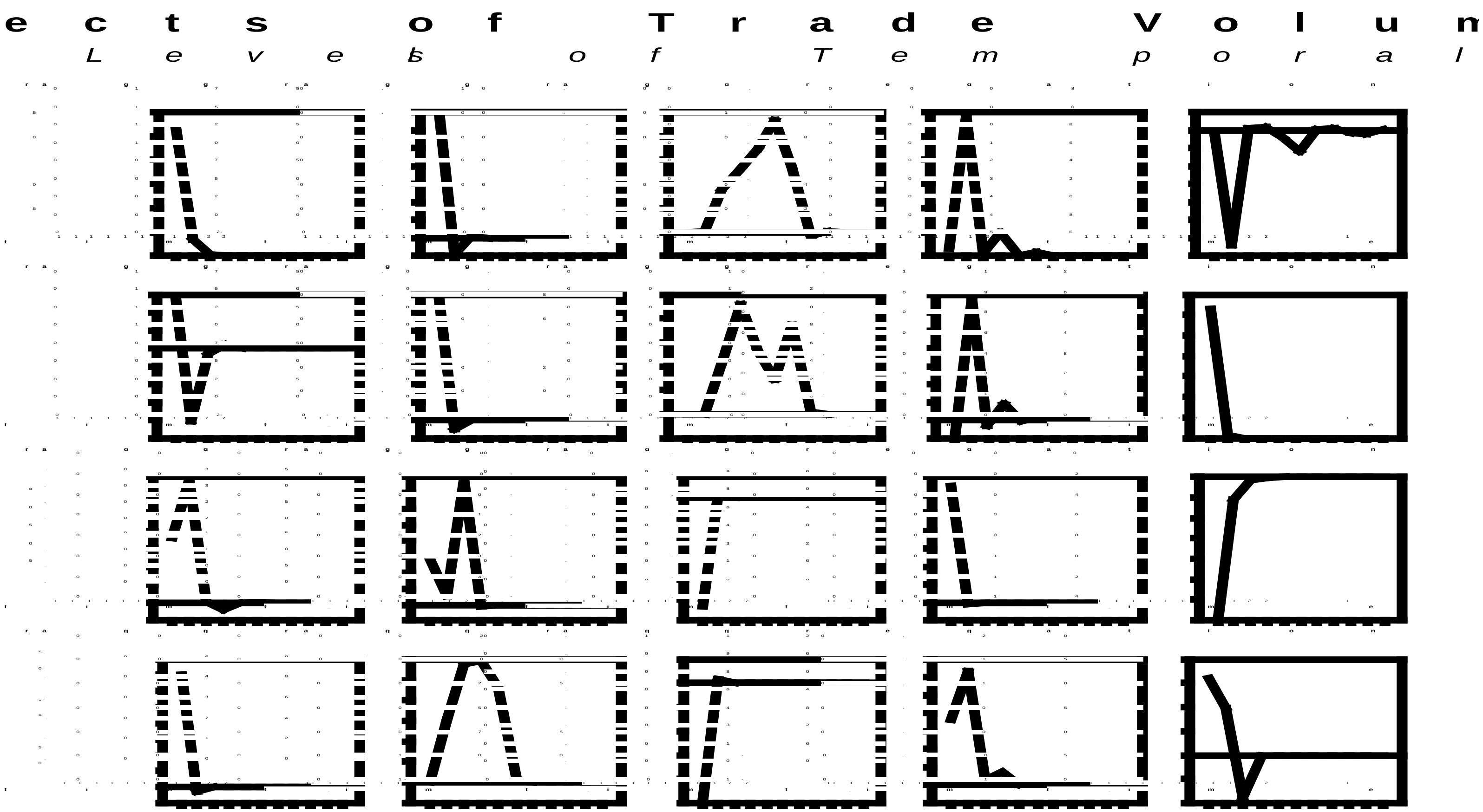

Figure 9. Diachronic effects of trade volumes to returns of ALFA Bank at different levels of Systematic Sampling.

5. Conclusions.

The results of this paper show the importance of temporal aggregation and systematic sampling in applied time series work. Temporal aggregation and systematic sampling causes a severe loss of information about the time series driving many economic variables. In this paper we analyse the effects of temporal aggregation and systematic sampling on detecting linear and nonlinear Granger causality relations among economic variables.

Using Monte Carlo techniques and an empirical application we may conclude that when we are interested to identify and to schematize nonlinear causalities between economic variables , is important to use our data in the highest level of temporal disaggregation.

As the span of aggregation widens, the time series properties are distorted, leading to wrong conclusions about linear and nonlinear effects between economic variables. Indeed, on the highest level of temporal aggregation, the likelihood of rejection of a true hypothesis approaches (100-4.86)% for temporal aggregation and (100-5.72)% for systematic sampling at a 0.025 significance level. The method of temporal aggregation also plays a crucial role. On the basis of our Monte Carlo results, it emerges that on short time aggregation levels, systematic sampling is two times more likely to accept the true hypothesis compared to temporal aggregation. The superiority of the systematic sampling method in accepting the true hypothesis is clear, at least at short time aggregation levels.

Lastly, the conclusions of this paper are in line with the more general findings of similar studies on the negative effects of time aggregation on the effectiveness of the statistical criteria for controlling the interdependencies between economic magnitudes.

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