# Trading Volume And Volatility:
# Intraday Evidence From The Athens Stock Exchange

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## Abstract

*With the present paper we document some standard statistical properties and 'stylized' facts of volume and volatility of nine common shares traded in the Athens Stock Exchange (ASE)\*\*\*. Using econometrical tools we investigate the relationship between volume and volatility attempting to find support for the Mixture of Distribution Hypothesis (MDH). Although the Granger-causality results can support a trading volume equation the well documented property of volatility clustering cannot be supported by the data. Furthermore, the trading volume seems to convey no information for the stock exchange participants. So we could cast doubt in the hypothesis proposed by Lamoureux and Lastrapes (1990).*

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## I.    Introduction

The relationship between volume and volatility has received considerable attention in the literature of financial economics (for an overview see Karpoff 1987). The importance of this relationship is directly related to the role of information in price formation and the efficiency of the market. Moreover, the efficient operation of the stock market has long been associated with the economic growth and the development.

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Recently, there is an increased use of market microstructure variables to test a number of hypotheses. The microstructure approach to the stock market is a result of the failure of the fundamental models to adequately explain the behaviour of the asset markets. The market microstructure literature is concerned with the relationship between information flows, the heterogeneity[1] of agent expectations and the implications of the latter for the volume and the price volatility; the former relationship has received a lot the most attention in the literature. However, only a small amount of work has been undertaken to assess the importance of these interrelationships in non-developed stock markets [2]

Purpose of this work is to test some econometric hypotheses which are somehow 'stylised' facts in the developed markets so as to assess the depth and the structure of the Athens Stock Exchange (ASE). This paper contributes to the literature in the following ways. Firstly, it contributes to the deep understanding of the interrelationships between the market microstructure variables into the ASE. Secondly, it will help toward the direction of specifying the exact nature of the volume-volatility relationship.

The outline of the paper is as follows. In the second section the previous empirical work and the relevant theoretical models are briefly reviewed. Section three describes some features of the data set used and some preliminary tests are applied.

The Granger-casuality tests are presented in the section four. In the firth section, by employing a conditional volatility class of model we try to investigate the informational nature of the trading volume. More specific we investigate the validity of the hypothesis proposed by Lamoureux and Lastrapes that the ARCH effects vanish when enter volume into the conditional variance equation. At the end, section sixth concludes.

## II.    Review Of Previous Theoretical And Empirical Work

The market microstructure story was initially developed to explain volume-volatility interrelationships for stock markets. The main part of empirical and theoretical work of these groups has been concentrated on the relationship between the measures of market microstructure variables. The earliest empirical examination which conducted by the micro literature concerned the relationship between the volume and the magnitude of the price change or the price change per se. Later Goodhart and Gingale (1983) and Wasserfallen and Zimmerman (1985) have observed systematic patterns of intraday volatility. They positively

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[1]    The heterogeneity as a microstructure variable has been modelled by Chionis and MacDonald (1987) and Chionis and MacDonald (1998).

[2]    Travlos (1996) used daily data of stocks returns for the period January 2, 1981 to December 31, 1990 review some of descriptive statistics.

relate the volatility with the unexpected volume. More recently another popular way of dealing with the time-varying variance of the returns is the ARCH models. Additionally, the information effects on the bid-ask spread is a subject of growing interest. The literature on the bid-ask spread (see Bessembinder (1994)) provides evidence on the determinants of the bid-ask spread in the foreign exchange market. This analysis supports the conclusions that the expected and unexpected components of trading volume have different effects in the conditional volatility.

Four groups of studies have developed to explain the interrelationships of the key market indicators. The first group may be labelled as the mixture of distribution hypothesis, (see *inter alia* Clark (1973), Epps and Epps (1976) and Tauchen and Pitts (1983)). Models testing this hypothesis are based on the assumption that the variance per transaction is monotonically related to the volume of that transaction and, further, it is assumed that a mixing variable is the cause of the joint volatility - volume relationship. Often in this type of research the number of information arrivals are designated as the mixing variable, although the volume per transaction and the number of transactions have also been designated as mixing variables. The theoretical research in this category predicts that volume is positively related to the magnitude of the corresponding price change over fixed time intervals or on a given transaction. Furthermore, these models can provide an explanation for the observed leptokurtosis of the speculative prices by assuming that the distribution of the rate of return appear kurtotic because the data are sampled from a mixture of distributions that have different conditional variances. Epps and Epps consider the variance of the price change on a single transaction is conditional upon the volume of that transaction. Transaction price changes are then mixture of distributions with volume as a mixing variable.

The second category of model is the sequential arrival of information view, developed and extended by Copeland (1976, 1977) and Jennings and Barry (1983). Copeland focused on the volume of asset trading. In an attempt to explain the positive relationship between volume and price change presents the sequential arrival of information process. This model assumes that information is disseminated sequentially from one group of traders to another and the individuals demand curve shift sequentially as new information is revealed to them. This sequential arrival of information creates numerous intermediate equilibrium prior to the final complete equilibrium. The change from one equilibrium level to another creates price changes at the same time as it generates volume.

The trading model of Admati (1988) and Brock and Kleidon (1992) are examples of the third category of model. In such models the focus is on the interrelatedness (although not causality) of bid-ask spreads, volume and volatility and, in particular, in explaining the U-shaped curves generated for both volume and volatility against the spread.

The fourth category includes the heterogeneus models of trader behaviour. Amongst this class of model the noise trader paradigm of De Long *et. al.* (1990) is the most representative (for a useful overview of this type of model and its

empirical implications see Chionis and MacDonald (1997). According to the noise trader model, trade is based on noise traders having a dispersion of expectations concerning the future value of the asset price and this, in turn, can generate considerable trading volume and price volatility as prices are driven far from their equilibrium values. Indeed, since in this model price conveys information to traders through chartist-type mechanisms, there is an important association between price volatility and volume.

Prior to the noise trader paradigm Pfleiderer (1984) considers the price volatility - trading volume relationship in circumstances where speculators have private information. According to this model, the magnitude of the price change is uncorrelated with trading by speculators with private information but is positively related to the trading by liquidity motivated investors. So, the strength of the correlation between price change and volume is negatively related to the existence of the private information. Since in the foreign exchange market there is no inside information the expected correlation between volume and volatility is expected to be strong. Related models are the models of Harris and Raviv (1993) and Shalen (1993) where the dispersion of beliefs/expectations determines volume and volatility through a two period noisy rational expectations model.

### III.    Data Definitions And Some Descriptive Statistics

The data set used by this study consists of a daily set of volume and volatility from 08/01/1994 to 04/03/1997 for nine common shares traded in the Athens Stock Exchange. These series are adjusted in order to take into account dividends, right issues and any other offer. In particular, we will investigate the time series properties of the following: Commercial Bank (empo), National Bank of Greece (ethn), Credit Bank (pist), Greek industry of sugar (ebz), Intracom (intra), Cement company TITAN (tita), 3E (triae), Balkan export (balex), for statistical purposes we also use the monotonic transformation with the prefix (l, i.e lempo=log(empo)), and the first differences which are denoted with dl (i.e. dlempo). We follow the same notation for trading volume time series having the prefix volume.

Before any statistical tests can be employed on the data set we must examine the stationarity properties of the data series. To this end, we use augmented Dickey-Fuller (1979) test statistics since they are considered the most appropriate to deal with variables with an autoregressive structure, which is the relevant case here, compared to, say, the unit root tests of Phillips and Perron (1988), and Choi and Phillips (1991) which suffer from serious distortions - see DeJong *et al.* (1992). In the table 1 we present the appropriate values of the Augmented Dickey Fuller test. According to these results, for the volatility of all examined shares we cannot reject the null hypothesis of a unit root. In contrast, all volume series (i.e. lvolumeempo) appear to be stationary.

## IV.    Tests of Market Microstructure Hypothesis - Empirical Results

In this section we implement some tests based on the market microstructure literature. As it is already mentioned, four competing hypotheses exist to explain any potential relationship between the market microstructure variables. In almost all of them suggested an association (sometimes correlation) between volume and volatility. The fact which remains unclear is the direction of causality if any. Across to this framework, we test the hypotheses relating to how volatility of prices drives the volume of shares and the opposite.

It has been well documented that volume and volatility and information flows are all highly contemporaneously correlated (for a review see Karpoff). From table 2 we can see the estimated cross correlation coefficient for the nine examine shares. In the first column we present the correlation among volatility and volume while the second column presents the estimated coefficient between the absolute value of volatility and volume. In contrast with the theoretical findings there are no evidence of significant correlation. A possible explanation is given by Chionis and MacDonald (1997). They propose two possible scenarios for the detected lack of correlation. According to the first, it has been argued that a potential non-linear relationship between volume and volatility cannot be traced by the standard serial tests. The second associated with possible asymetricities in the relationship between volume and volatility causing a changing relationship in various estimated intervals of observation.

In testing the interrelationship between volume and volatility we use Granger-causality methods. The Granger procedure is chosen because it has the advantage of offering a powerful, yet simple, way of testing causality. We start first by estimating bivariate relationships of the following from:

$$\boxed{vol_t = \sum_{t=1}^{p} vol_{t-1} + \sum_{t=1}^{p} volu_{t-1} + e_t} \tag{1a}$$

and

$$\boxed{volu_t = \sum_{t=1}^{p} volu_{t-1} + \sum_{t=1}^{p} vol_{t-1} + e_t} \tag{1b}$$

where $vol_t$ denotes share volatility, $volu_t$ denotes volume and $\varepsilon_\tau$ denotes a random error term. $vol_t$ is deemed to Granger-cause $volu_t$ if the sum of the lags terms are jointly signifcant in (1b) and the lagged $vol$ terms in (1a) are jointly zero. Bi-directional causality occurs when the sum of the lags on $vol_t$ or $volu_t$ are jointly significant in (1a) or (1b). In testing the joint significance of the lagged terms it is standard practice to use a conventional F-statistic. Here, because of the assumed heteroscedasticity in the data, we use linear Wald test statistics which incorporate a White-Hansen correction for heteroscedasticity. That is the variance covariance matrix of the has the following form:

$$(X'X)^{-1}\text{mcov}(X,u)(X'X)^{-1}$$

where mcov(X,u) refers to the following matrix

$$\sum_{K=-L}^{L} \sum_{T} u_t X_T' X_{t-K} u_{t-K}$$

In table 3 we present our Granger-causality tests for the relationship between volume and volatility. The results are quite striking in the sense that volatility Granger - causes volume at the five percent level in all instances. Interestingly, there appears to be no any reverse causality in that Volume Granger-causes volatility.

## V.     A Time Series Approach to Volatility and the Informational Content of Volume

In this section we examine the statistical properties of the rates of change of the nine shares considered in the previous sections and, in particular, we estimate a set of GARCH models to obtain estimates of conditional volatility. The purpose of this exercise is to test a number of hypotheses related to those considered in previous sections. We test, first, whether conditional variance can serve as a good proxy for trading volume. This is an hypothesis first proposed by Lamoureux and Lastrapes (1990) who tested it using stock market data. The authors use volume as a proxy for information arrival and they showed that this proxy has significant explanatory power regarding the conditional variance of daily returns. In particular, for a sample of 20 US common stocks returns, they find that ARCH effects vanish when volume is included as an explanatory variable into the conditional variance equation. We propose testing this hypothesis with our data set.

### i.   GARCH Models

Before implementing our set of hypothesis tests based on conditional volatility we first have to determine if the GARCH class of model can be used to capture the stylised facts of short-run exchange movements, such as their contiguous periods of volatility and stability, together with the leptokurtotic unconditional distribution normally observed for such data sets. The basic ARCH model of Engle (1982), and its extension to the GARCH framework by Bollerslev (1986), has been shown to provide a good fit for many financial returns time series. It allows one to model a process with changing variance in a strictly univariate framework, while at the same time providing an explanation of leptokurtosis often observed in financial data. The idea is to distinguish between the

(changing) conditional and the (constant) unconditional variance of the process, and to hypothesise that the former is autocorrelated over time and hence forecastable on the basis of past realisations of the process in a manner similar to that of the conditional mean in an ARMA process. ARCH imposes an autoregressive structure on the conditional variance, allowing volatility shocks to persist over time. This persistence captures the propensity of returns of like magnitude to cluster in time and can explain the well documented non-normality and nonstability of empirical asset return distributions (Fama 1965).

In generating our GARCH models, we employ a two stage estimation procedure in which the conditional mean is first formulated as an ARIMA process and then the conditional variance of the spot exchange rate is estimated as a GARCH process. Since each of the logarithmic values of the price series seem to contain a unit root (but not the first difference), we focus on percentage returns as the relevant series. To identify the time series behaviour of the mean we employ some standard time series tests; in particular, the autocorrelation function, partial autocorrelation function and the statistical significance of additional terms used to identify and check the time series behaviour of the conditional mean. Summary statistics for the different daily returns series are reported in the table 4.

We test the null hypothesis that shares' returns are pure integrated process of order one i.e. ARIMA (0,1,0) against the alternative of an ARIMA (p,1,q), with at least one of p and q non-zero. Using the heteroskedasticity consistent estimate of the standard error due to Diebold (1986), we note that none of the autocorrelations are statistically significant.[3] This finding is confirmed by the adjusted Box-Pierce Q statistics, reported in Table 9c.[4] Summing up, these different statistics indicate the absence of serial correlation. The results are further confirmed by the Graph 1 and 2. Together with insignificant means, the statistics suggest a random process. The excess kurtosis evident in all currency returns is a feature of other previous theoretical work on daily returns and indicates a fat-tailed distribution. Taking into consideration the above points we approximate the percentage nominal return on share i obtained from dates t-1 to t as $A_t = 100[\log s_{it} - \log s_{it-1}]$. The conditional mean equation has the form:

$$\boxed{A_t = \mu + \varepsilon_t} \, , \tag{2a}$$

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[3]   This is defined as: $S(k) = \sqrt{[(1/T) (1 + \gamma(k)/\sigma^4)]}$ where $\gamma(k)$ is the autocovariance at lag k of the squared data and $\sigma$ is the sample standard deviation of the data. Using unadjusted Bartlett standard errors we did find evidence of statistically significant autocorrelations; however, given the evident heteroscedasticity in the data we do not consider these to be reliable.

[4]   This statistic is defined as: $\sum_{k=1}^{K} [\gamma(k)/S(k)]^2$ and has an asymptotic chi-square distribution, with k degrees of freedom.

and the conditional variance

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \sigma_{t-1}^2 + a_3 \text{volu}_{t-1},$$   (2b)

and

$$\varepsilon_t / \Psi_{t-1} \approx N(0, \sigma_t^2), \quad t = 1, 2 \ldots T.$$   (2c)

where $\Psi_{t-1}$, denotes the time t-1 information set and $\mu$, $a_0, a_1, a_2$ and $a_3$ are parameters to be estimated.

The GARCH(1,1) structure in equation (2a) is used to model autonomous movements in the conditional variance. We fit a low order GARCH so as to avoid having to deal with the complexities relating to potentially negative or zero coefficients, or to the possibility that the sum of the coefficients is greater than one. We maintain the assumption on traders' information embodied in equation (2c) by using lagged information on market activity and the dispersion of expectations to explain conditional volatility movements. We also rely on the result of Nelson (1992) that conditional variance estimates, using high frequency data, converge to the true conditional variance and can be used to estimate the variance very precisely. Additionally, Nelson (1992) shows that if the true model is a diffusion model with no jumps, then the discrete time variance are consistently estimated by a GARCH (1,1).[5]

Table 5 reports Full Information Maximum Likelihood estimates using the Berndt, Hall, Hall, and Hausman (1974) (BHHH) algorithm. Engle (1982) shows that the efficiency of Maximum-Likelihood estimation relative to least-squares is positive and may be very large, so we apply the former, using the latter only to provide starting values for the estimated parameters. Given the severe kurtosis and heteroskedasticity present in the data, conventional standard errors will have questionable value. However, Baillie and Bollerslev (1990) have shown that in the present model with homoskedastic errors suitable robust standard errors may be obtained using the correction of White (1982),[6] and these are used in the present application. According to the robust standard errors, the results are rather disappointing in the sense that the coefficients of the lag variance are statistical insignificance. In some of the cases the coefficients of the lagged errors are statistical significant. This observation give rise to attempt an

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[5] Further justification for the use of GARCH instead of ARCH or other extensions can be found in the recent findings of K. West and D. Cho (1995). The authors, by testing the predictive ability of several models of exchange rate volatility, prove that GARCH and IGARCH models have the best performances.

[6] Following White, asymptotic standard errors for the parameters in the conditional mean and variance functions that are robust to departures from normality have also been derived by Weiss (1984,1985).

ARCH (1) model. Again the results are not changing as regard the statistical significance. These findings fail to document the property of many financial series that 'news' clusters in time i.e. periods of large absolute changes tend to cluster together followed by periods of relatively small absolute changes.

Tending to change the results and to document simultaneously the effect of trading volume on the conditional variance, we also incorporate the past volume into the equation of conditional volatility. Interestingly, the estimations are remaining unchanging (the similar results have been derived by Chionis and MacDonald 1997). In addition it is interesting to note that the volume enters insignificantly into the conditional volatility equation.

## VI.    Conclusions

In this work we investigate the validity of some well documented hypotheses on the ASE. We focused on volume and volatility of nine selective shares. The result of estimating the causal relationships suggest that we can support a structural form analysis having as dependent variable the volume and independent the volatility.

A proposed direction for improving the results could be the incorporation of expected trading into the conditional volatility equation. Since the volume data is highly forecasted we expect to improve the statistical significant of the equation. Apart from the econometrical results a number of interesting implications arises from this work. The property of volatility clustering seems to not be supported by the data. In addition, volume appears to be influenced by the volatility and not the opposite. This finding is further supported by the conditional volatility findings.

At the end it should be noted that an interesting related hypothesis, which can follow on from our discussion is: does the bid ask spread enters significantly into the GARCH relationship.

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# Table 1

*Unit Root Tests*

| Series | t-trend | t |
|---|---|---|
| Pisteos{7} | -1.17 | |
| Q | 18.2 | |
| dlpisteos{1} | -9.95 | -9.961 |
| Q | 14.06 | 12.0 |
| ltrae | -2.242 | -0.54 |
| Q | 20.7 | 19.0 |
| dltrae | -8.34 | -8.31 |
| Q | 19 | 18.6 |
| lpetz | -3.37 | -2.20 |
| Q | 20.6 | 20.4 |
| dlpetz | -7.73 | -7.77 |
| Q | 17 | 20 |
| lebz{8} | -1.85 | -2.26 |
| Q | 15 | 15 |
| dlebz{1} | -10.32 | -10.16 |
| Q | 15.2 | 14 |
| ltita{1} | -1.16 | -0.739 |
| Q | 17.3 | 17.32 |
| dltita{1} | -9.69 | -9.56 |
| Q | 18.97 | 17.76 |
| lbalex{1} | -2.81 | -1.52 |
| Q | 18.4 | 19.16 |
| dlbalex | -11.38 | -11.3 |
| Q | 10.3 | 9.3 |
| lempo{1} | 1.8 | |
| Q | 14.5 | |

| Series | t-trend | t |
|---|---|---|
| dlempo | -8.58 | -8.25 |
| Q | 10.2 | 10.8 |
| lethn{1} | -1.77 | -1.531 |
| Q | 12.6 | 13.0 |
| dlethn{1} | -9.15 | -9.02 |
| Q | 14.66 | 13.98 |
| lintra | -0.96 | -1.25 |
| Q | 13.4 | 8.76 |
| dlintra | -.4.21 | -5.8 |
| Q | 10.32 | 7.94 |
| lindex | -2.05 | -2.33 |
| Q | 20.9 | 20.5 |
| dlindex | -7.90 | -7.27 |
| Q | 18.8 | 18.7 |
|  |  |  |
| lvolumeintra | -5.79 | -5.261 |
| lvolumeebz | -6.75 | -6.67 |
| lvolumepetz | -7.498 | -7.17 |
| lvolumepist | -6.90 | -5.49 |
| lvolumetita | -5.70 | -6.49 |
| lvolumetriae | -8.23 | -8.67 |
| lvolumebalex | -5.17 | -3.74 |
| lvolumeempo | -5.72 | -4.60 |
| lvolumeethn | -6.41 | -4.87 |
| lvolumeindex | -6.25 | -4.13 |

## Table 2

*Cross correlation tests*

|            | *CORR(DP,VOL)* | *CORR(ABS(DP),VOL)* |
|------------|----------------|---------------------|
| TRIAE      | 0,037          | 0,004               |
| EBZ        | 0,031          | -0,05               |
| BALEX      | 0,006          | 0,013               |
| EBORIKI    | -0,06          | 0,07                |
| INTRACO    | 0,000          | 0,018               |
| PETZETA    | 0,020          | -0,05               |
| PISTEOS    | 0,06           | 0,00                |
| ETHNIKI    | -0,02          | 0,013               |
| TITAN      | -0,003         | 0,03                |

# Table 3

*Granger-Causality*

| causality direction | Chi-square |
|---|---|
| ldvolaempo→lvolumempo | 46.684 |
| | (0.000) |
| lvolumempo ↦ ldvolaempo | 1.292 |
| | (0.992) |
| dlpist→lvolumepist | 26.807 |
| | (0.000) |
| lvolumepist ↦ dlpist | 1.362 |
| | (0.999) |
| dltriae→ lvolumetriae | 23.225 |
| | (0.003) |
| lvolumetriae↦dltriae | 1.572 |
| | (0.991) |
| lvolumeebz→dlebz | 32.743 |
| | (0.000) |
| dlebz↦ lvolumeebz | 1.231 |
| | (0.299) |
| dlintra→ lvolumeintra | 40.719 |
| | (0.000) |
| lvolumeintra ↦dlintra | 1.687 |
| | (0.989) |
| dlethn→lvolumeethn | 48.067 |
| | (0.000) |
| lvolumeethn↦ dlethn | 1.429 |
| | (0.993) |
| dlpetz →lvolumepetz | 17.089 |

| causality direction | Chi-square |
|---|---|
| | (0.029) |
| lvolumepetz↦dlpetz | 1.94 |
| | (0.982) |
| dlbalex→lvolumebalex | 41.401 |
| | (0.000) |
| lvolumebalex ↦ dlbalex | 5.183 |
| | (0.737) |
| dltita → lvolumetita | 38.409 |
| | (0.000) |
| lvolumetita ↦ dltita | 1.364 |
| | (0.994) |
| dlindex →lvolumeindex | 72.499 |
| | (0.000) |
| lvolumeindex ↦ dlindex | 1.233 |
| | (0.996) |

**Table 4**

*Descriprictive statistics*

|          | mean     | variance | kurtosis | skewness  |
|----------|----------|----------|----------|-----------|
| Dlpist   | -0.005   | 0.027    | 664.8    | -25.763   |
|          | (0.165)  |          |          |           |
| Dltriae  | -0.005   | 0.023    | 664.462  | -25.752   |
|          | (0.152)  |          |          |           |
| Dlpetz   | -0.004   | 0.0145   | 658.592  | -25.581   |
|          | (0.120)  |          |          |           |
| Dlebz    | -0.005   | 0.0165   | 660.358  | -25.633   |
|          | (0128)   |          |          |           |
| Dltita   | -0.005   | 0.027    | 664.970  | -25.767   |
|          | (0.167)  |          |          | -25.754   |
| Dlbalex  | -0.003   | 0.008    | 638.667  | -24.998   |
|          | (0.184)  |          |          |           |
| Dlempo   | -0.005   | 0.156    | 663.650  | -25.729   |
|          | (0.156)  |          |          |           |
| Dlethn   | -0.005   | 0.029    | 664.517  | -25.754   |
|          | (0.172)  |          |          |           |
| Dlintra  | -0.005   | 0.023    | 661.081  | -25.654   |
|          | (0.154)  |          |          |           |

*Standard errors are in parentheses*

**Table 5**

*GARCH Results*

| | $a_0$ | $a_1$ | $a_2$ |
|---|---|---|---|
| dlpist | -0.066* | 0.017 | -1.075 |
| | (0.032) | (0.013) | (2.420) |
| Funct. Value | 824 | | |
| dltriae | -0.136* | -0.136* | 0.046 |
| | (0.056) | (0.088) | (4.253) |
| Funct. Value | 673 | | |
| dlpetz | -0.739* | -0.026* | 1.73 |
| | (0.088) | (0.011) | 0.93 |
| Funct. Value | 730 | | |
| dlebz | 0.061* | 0.053* | -0.769* |
| | (0.004) | (0.005) | (0.38) |
| Funct. Value | 783 | | |
| dltita | 0.037* | 0.011* | -2.870* |
| | (0.0004) | (0.002) | (0.371) |
| Funct. Value | 650 | | |
| dlbalex | -0.007 | 0.036* | 0.125 |
| | 0.113 | 0.005 | 10.756 |
| Funct. Value | 795 | | |
| dlempo | -0.037 | 0.046* | 0.121 |
| | (0.246) | (0.020) | (8.413) |
| Funct. Value | 767 | | |
| dlethn | -0.006* | 0.046* | 0.081 |
| | (0.001) | (0.013) | (8.77) |
| Funct. Value | 782 | | |
| dlintra | -0.103 | 0.053 | -0.263 |
| | (0.106) | (0.039) | (3.122) |
| Funct. Value | 729 | | |

*\* Denotes statistical significance at 5%.*

# Table 6

*GARCH (1,1),volume results*

|  | $a_0$ | $a_1$ | $a_2$ | $a_3$ |
|---|---|---|---|---|
| dlpist | -0.066* | 0.017 | -1.075 | 0.0006 |
|  | 0.032 | 0.013 | 2.420 | (0.55) |
| Funct. Value | 824 |  |  |  |
| dltriae | -0.136* | 0.029 | 0.046 | 0.0004 |
|  | 0.056 | 0.088 | 4.253 | 0.095 |
| Funct. Value | 840 |  |  |  |
| dlpetz | -0.48* | 0.062* | -2.6 | 0.0008 |
|  | (0.01) | (0.004) | (8.63) | (0.037) |
| Funct. Value | 738 |  |  |  |
| dlebz | -0.074* | 0.082* | 0.3 | 0.0005 |
|  | (0.0052) | (0.025) | (6.8) | (0.1) |
| Funct. Value | 812 |  |  |  |
| dltita | 0.0375* | 0.011* | -2.870* | 0.008 |
|  | 0.0004 | 0.002 | 0.371 | 0.001 |
| Funct. Value | 650 |  |  |  |
| dlbalex | -0.007 | 0.036* | 0.125 |  |
|  | 0.113 | 0.005 | 10.756 |  |
| Funct. Value | -0.037 | 0.046 | 0.121 | 0.0002 |
| dlempo | 0.246 | 0.020 | 8.413 | (1.84) |
| Funct. Value | 767 |  |  |  |
| dlethn | -0.029 | 0.046* | 0.081 | 0.056 |
|  | 0.169 | 0.013 | 8.779 | 0.65 |
| Funct. Value | 782 |  |  |  |
| dlintra | -0.103 | 0.053 | -0.263 | 0.00035 |
|  | 0.106 | 0.039 | 3.122 | (0.48) |
| Funct. Value | 729 |  |  |  |

# Figure 1

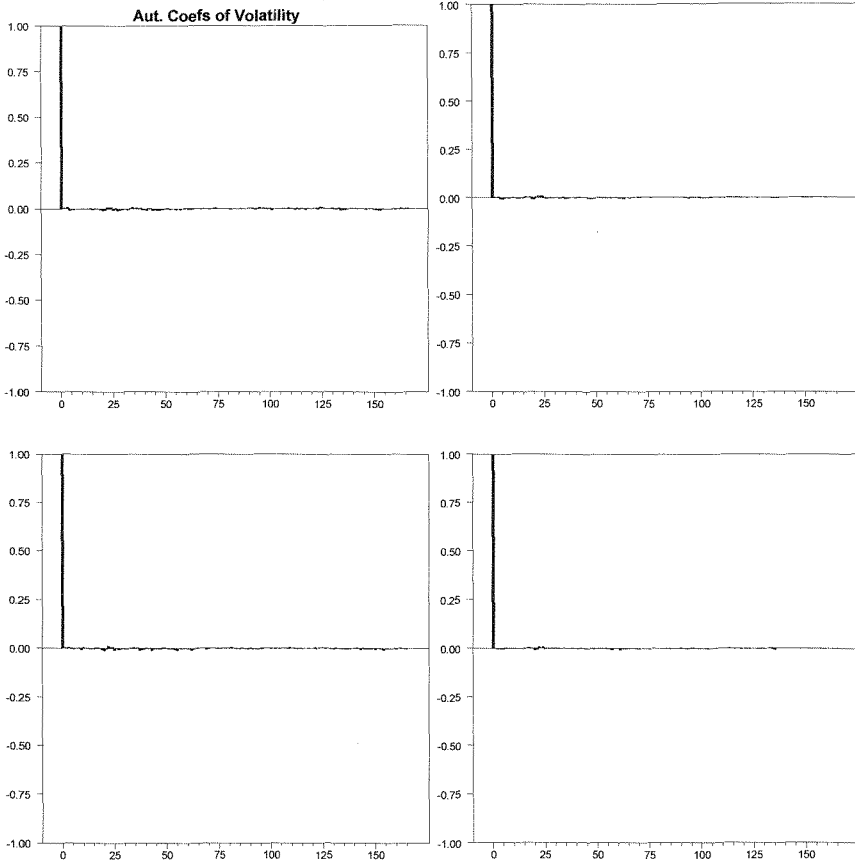*Autocorrelation Coefficients of dlempo,dlethn,lebz, dlindex*

# Figure 2

*Autocorrelation Coefficients of dlitr, dlpetz, dlpist, dltita, dltrae, dlbalex*
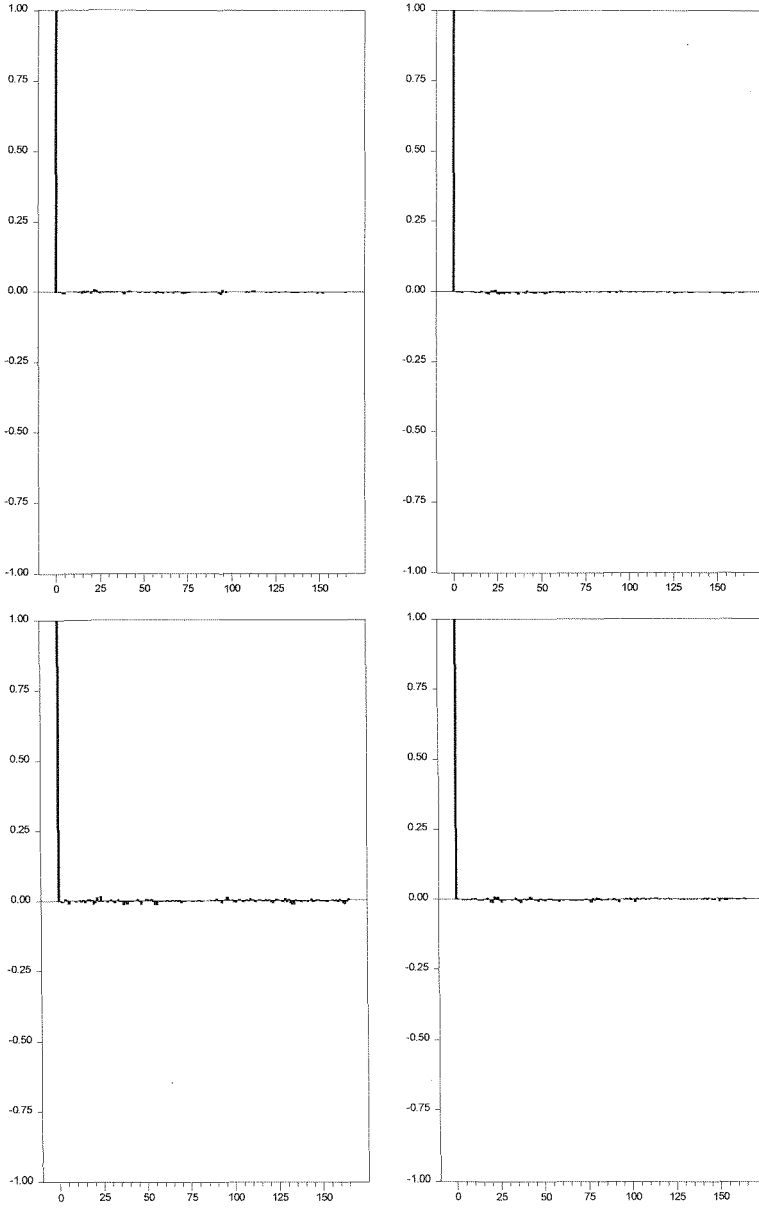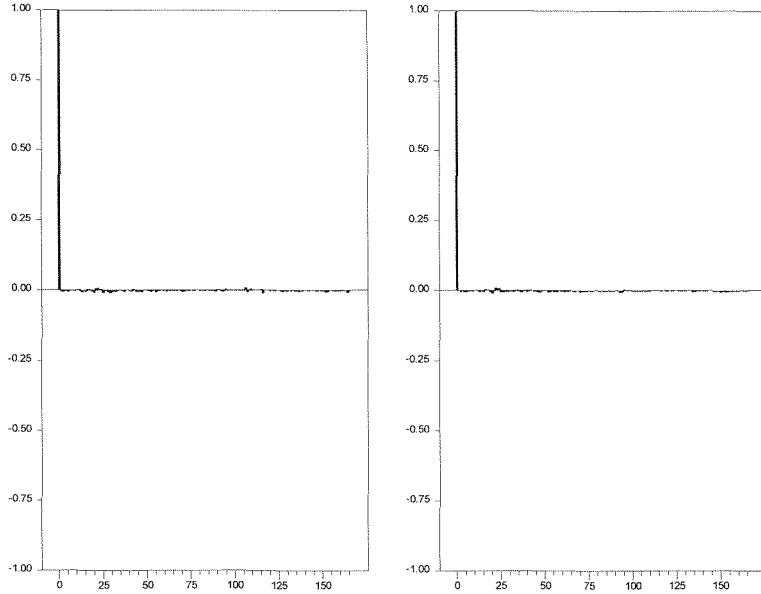
**Figure 2 (cont.)**

*Autocorrelation Coefficients of dlitr, dlpetz, dlpist, dltita, dltrae, dlbalex*



| | CORR(INDEX,CLOSE) |
|---|---|
| 3E | 0,6341 |
| EBZ | -0,335 |
| BALEX | -0,219 |
| EBORIKI | 0,778 |
| INTRACO | 0,336 |
| PETZETA | 0,0032 |
| PISTEOS | 0,869 |
| ETHNIKI | 0,927 |
| TITAN | 0,844 |