CHAPTER 3

3. Empirical Evidence from the Greek Stock Market. A Preliminary Analysis

The data set we will analyze (we are grateful to GrStocks.com for providing the data) is the General Index of Athens Stock Exchange (hereafter GI). There are totally 2982 observations from 31 July 1987 to 30 July 1999.

Define

$$y_t = \log\left(\frac{p_t}{p_{t-1}}\right)$$

as the continuously compounded rate of return for GI at time t $(t = 1,...,2981)$, where p_t is the daily closing price of GI. The descriptive statistics for y_t are presented in Table 3.1.

Table 3.1								
Summary Statistics of y_t								
Sample Size	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque Bera
2981	0.000997	0.00035	0.24227	-0.1629	0.020398	0.38694	16.3209	22114.6

The kurtosis of 16,32 if far beyond that of normal distribution that is 3. Jarque-Bera is a test statistic for testing whether the series is normally distributed. The Jarque-Bera test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The statistic is computed as:

$$JB = \frac{N-k}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right)$$

where S is the skewness, K is the kurtosis, and k represents the number of estimated coefficients used to create the series. Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as X^2 with 2 degrees of freedom. The null hypothesis of normality is rejected at any critical value.

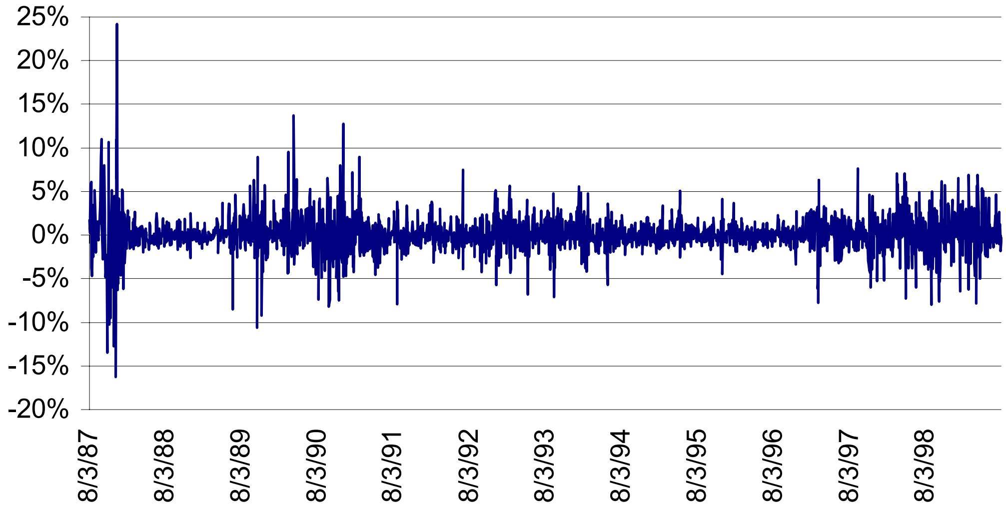
Figures 3.1 and 3.2 plot the p_t and y_t respectively. The p_t is an upward trending clearly non-stationary series. On the other hand the y_t is a rather stable process around its mean 0,000997 but with non-constant variance over time. We can clearly see that these data satisfy the observation of Mandelbrot (1963), who wrote "… large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes…" The market volatility is changing over time, which suggests a suitable model for the data should have a time varying volatility structure.

Figure 3.1
Daily Closing Prices of Athens Stock Exchange General Index
31 July 1987 - 30 July 1999

Figure 3.2

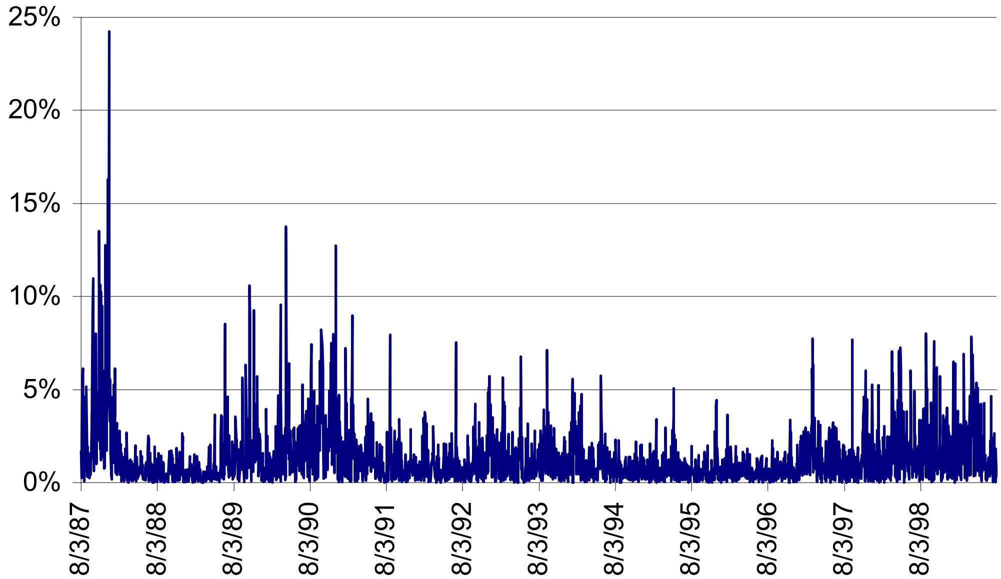
Continuously Compounded Daily Returns for Athens Stock Exchange General Index

1 August 1987 - 30 July 1999



Volatility clustering phenomenon is even more obvious when the absolute return s are plotted through time. Figure 3.3 plots the $|y_t|$.

Figure 3.3
Absolute Continuously Compounded Daily Returns of Athens
Stock Exchange General Index
1 August 1987 - 30 July 1999



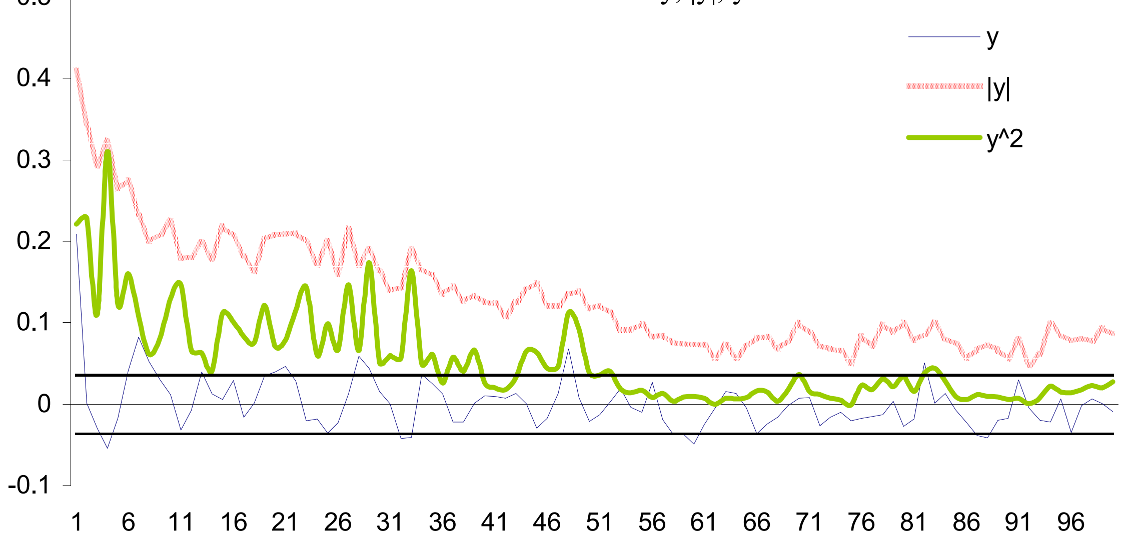
According to efficient financial market theory, the stock market returns themselves contain little serial correlation (Fama (1970)). Taylor (1986) studied the correlations of the transformed returns for 40 series and concluded that the returns process is characterized by more correlation between absolute and squared returns than there is between the returns themselves. Table 3.2 shows the autocorrelation of y_t, $|y_t|$ and y_t^2 for lags 1 to 100. Figure 3.4 plots the autocorrelation function of y_t, $|y_t|$ and y_t^2.

Table 3.2
Autocorrelations of y_t, $|y_t|$ and y_t^2

Data	lag 1	lag 2	lag 3	lag 4	Lag 5	lag 10	Lag 20	lag 40	lag 70	lag 100
y_t	0.209	0.001	-0.030	-0.055	-0.018	0.012	0.039	0.010	0.007	-0.009
$\|y_t\|$	0.410	0.344	0.293	0.324	0.265	0.225	0.208	0.125	0.100	0.086
y^2	0.221	0.229	0.110	0.310	0.123	0.129	0.071	0.026	0.036	0.027

Figure 3.4

Autocorrelation function of y, |y|, y^2



The straight lines in Figure 3.4 show the 95% confidence interval, which is equal to $\pm 1{,}96\sqrt{\mathrm{T}}$, for the estimated sample autocorrelation if the process y_t is independent and identically distributed (hereafter i.i.d.). The 21% of the autocorrelations are outside the 95% confidence interval for an i.i.d. process. Moreover, if y_t is an i.i.d. process, then any transformation of y_t is also an i.i.d. process. This clearly does not hold for the y_t, thus, the GI return is not an i.i.d. process.

Ding et al. (1993) examine the autocorrelation of $|y_t|^d$ for positive d where y_t is the S&P500 daily continuously compounded return. They found that all the power transformations of the absolute returns have significant positive autocorrelations at least up to lag 100, which supports the claim that the stock returns have long-term memory. They also found that the autocorrelations are a smooth function of d. Monte Carlo studies show that the ARCH models with appropriate parameters can produce the special correlation patterns of the S&P 500 return series. We examine the sample autocorrelations of the transformed absolute GI returns $|y_t|^d$ for various positive d. Table 3.3 shows the $Corr\left(|y_t|^d, |y_{t+\tau}|^d\right)$ for d = 0.1, 0.2, 0.3, 0.5, 0.7, 1, 1.2, 1.5, 1.7, 2, 3 and lags 1 to 100.

Table 3.3

$Corr\left(|y_t|^d, |y_{t+\tau}|^d\right)$ for d = 0.1, 0.2, 0.3, 0.5, 0.7, 1, 1.2, 1.5, 1.7, 2, 3 and lags 1 to 100

D	0.1	0.2	0.3	0.5	0.7	1	1.2	1.5	1.7	2	3
lag 1	0.289	0.328	0.354	0.391	0.411	0.410	0.390	0.337	0.292	0.221	0.061
lag 2	0.257	0.295	0.316	0.341	0.351	0.344	0.329	0.296	0.270	0.229	0.111
lag 3	0.240	0.271	0.289	0.311	0.316	0.293	0.262	0.204	0.164	0.110	0.021
lag 4	0.212	0.252	0.275	0.304	0.318	0.324	0.322	0.317	0.315	0.310	0.265
lag 5	0.213	0.245	0.262	0.282	0.284	0.265	0.240	0.196	0.165	0.123	0.038
lag 10	0.147	0.174	0.192	0.216	0.227	0.225	0.214	0.187	0.165	0.129	0.043
lag 20	0.144	0.172	0.190	0.214	0.222	0.208	0.186	0.142	0.112	0.071	0.009
lag 40	0.140	0.156	0.163	0.164	0.153	0.125	0.102	0.067	0.048	0.026	0.001
lag 70	0.084	0.100	0.109	0.116	0.114	0.100	0.087	0.066	0.053	0.036	0.008
lag 100	0.084	0.091	0.095	0.099	0.098	0.086	0.074	0.054	0.042	0.027	0.005

Figure 3.5 plots the auto-correlogram of $|y_t|^d$ from lag 1 to 100 for d = 0.1, 0.2, 0.3, 0.5 in Figure 3.5.1, for d = 0.7, 1, 1.2 in Figure 3.5.2 and for d = 1.5, 1.7, 2 in Figure 3.5.3.

Figure 3.5.1

Autocorrelation of |y|^d for d = 0.1, 0.2, 0.3, 0.5

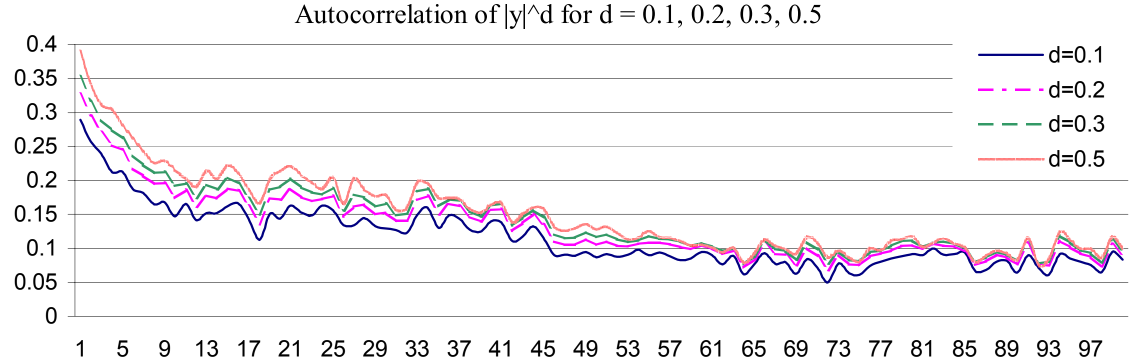


Figure 3.5.2

Autocorrelation of |y|^d for d =0.7, 1, 1.2

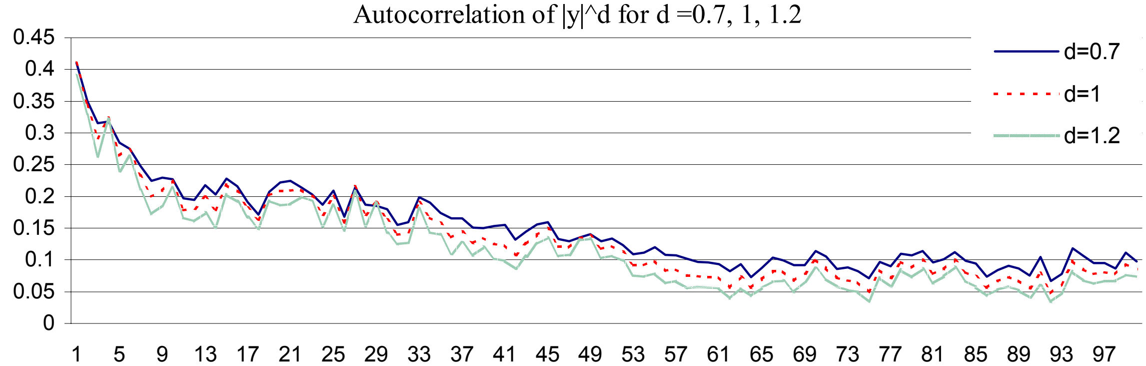
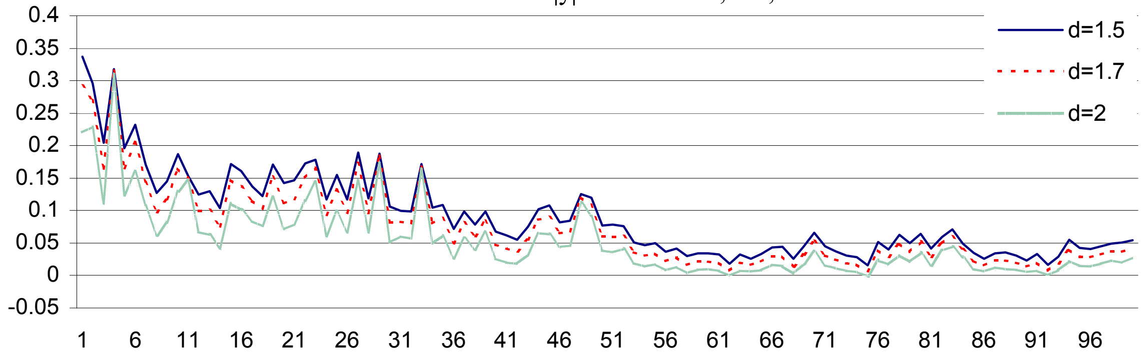


Figure 3.5.3

Autocorrelation of |y|^d for d =1.5, 1.7, 2



The autocorrelations decrease fast in the first trading days and then decrease very slowly. A very interesting finding from the Table 3.3 is that the autocorrelations has the largest value for d=1 and then decrease monotonically. Figure 3.6 shows a 3 dimensional plot of $Corr\left(|y_t|^d, |y_{t+\tau}|^d\right)$. Figures 3.7.1, 3.7.2, 3.7.3 and 3.7.4 give the plots of $Corr\left(|y_t|^d, |y_{t+\tau}|^d\right)$ at τ =1, 2, 5, 10.

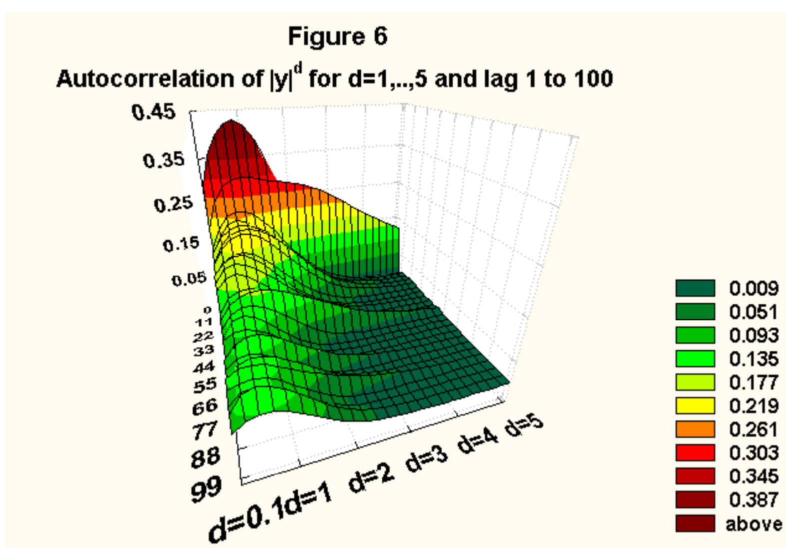


Figure 6

Autocorrelation of $|y|^d$ for d=1,..,5 and lag 1 to 100

It is clear from these figures that the autocorrelation function is a smooth function of *d*. For each τ there is a unique point d^* between 0.4 and 0.8 such that $Corr\left(\left|y_t\right|^d, \left|y_{t+\tau}\right|^d\right)$ reaches its maximum at this point, $Corr\left(\left|y_t\right|^{d*}, \left|y_{t+\tau}\right|^{d*}\right) > Corr\left(\left|y_t\right|^d, \left|y_{t+\tau}\right|^d\right)$ for each *d*. Also, for each τ there is a unique point d' between 2 and 3 such that when $d < d'$ the $Corr\left(\left|y_t\right|^d, \left|y_{t+\tau}\right|^d\right)$ is a concave function and when $d > d'$ the $Corr\left(\left|y_t\right|^d, \left|y_{t+\tau}\right|^d\right)$ is a convex function of d.

Figure 3.7.1 Autocorrelation of |y|^d at lag 1

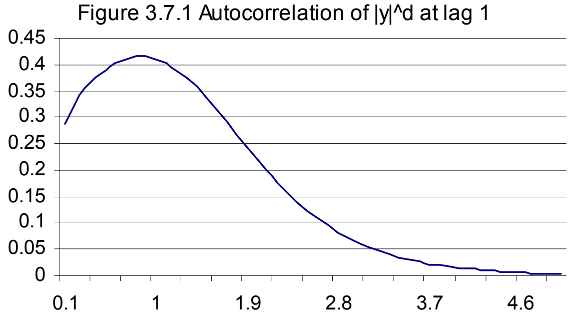


Figure 3.7.2 Autocorrelation of |y|^d at lag 2

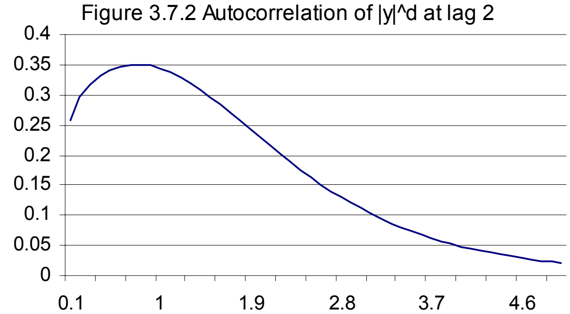


Figure 3.7.3 Autocorrelation of |y|^d at lag 5

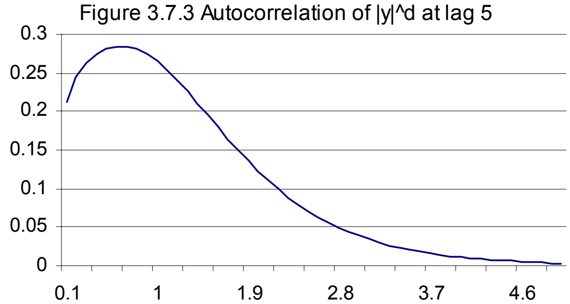
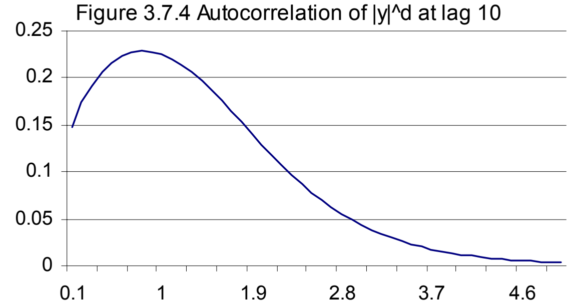


Figure 3.7.4 Autocorrelation of |y|^d at lag 10



The GI returns exhibits almost identical pattern to S&P 500 returns, thus the returns of the Greek Stock Market are characterized by long-term memory pattern.