European Research Studies
Vol. III, Iss. (3-4), 2000, pp. 3-15

Volatility Behaviour in Emerging Markets: A Case Study of the Athens Stock Exchange, Using Daily and Intra-Daily Data

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Abstract

In this paper we study the volatility behaviour, the aggregation effects and we investigate the nature of shocks coming disturb the Greek Market. To do so, we apply the ARCH LM, the fractional integration (Geweke and Porter-Hudak, 1983) and the R/S (Lo, 1991) tests, to daily and intra-daily data. The findings support trading-day effects in intra-daily series, and for this reason we prefer examining the source of shocks by estimating only the daily returns with a GARCH(p,q)-M model. The obtained results show that endogenous factors, such as local information, play a more important role in emerging that in developed Stock Exchanges.

Key words: aggregation, daily and intra-daily data, volatility, short and long memory, GARCH(p,q)-M model, emerging stock markets.

JEL Classification: G12, C52.

1. Introduction

Numerous papers have investigated the stochastic behaviour of stock returns of major national stock markets. Smaller markets, on the other hand, have not received the same attention. The capital markets in developing economies, namely Emerging Capital Markets (henceforth ECM), is of interest to both investors and multinational enterprises, because they constitute important conduits for further diversification in the light of recent evidence concerning the integration and increased co-movement of major capital markets. If higher co-movement translates into higher correlations across major capital markets, then individual and institutional investors should explore the opportunities offered by the ECM, which are not as yet integrated with the developed capital markets (henceforth DCM).

The nature of dynamics of stock returns in ECM is therefore of great interest. ECM exhibit characteristics different from those observed in DCM. Biases due to market thinness and non-synchronous trading should be expected to be more severe in the case of ECM. Also, in contrast to DCM, which are highly

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efficient in terms of the speed of information, investors tend to react slowly and gradually to new information. One such ECM is the Greek stock market.

Nevertheless Greek authorities are committed to modernising and liberalising the Athens Stock Exchange (hereafter ASE) in order to increase its efficiency and make it more accessible to international investors. The new reforms that were introduced by the L.1806/88 stock exchange law have affected the market positively and leaded to the expansion of its activity. The introduction of new financial instruments, like warrants, options, commercial paper etc. are currently under way. We must note that there is no capital gains tax in Greece.

In this paper we study the volatility behaviour, the aggregation effects and we investigate the nature of shocks that disturb the Greek stock market. Since we are interested in the intra-daily market activity, volatility is calculated only for the intra-daily series. The findings support trading-day effects in intra-daily series, and for this reason we prefer examining the source of shocks by estimating only the daily returns with a GARCH-M model. The choice of a such model is also confirmed by applying the ARCH LM and memory tests to both daily and intra-daily aggregated series.

The plan of the paper is as follows. In section 2 we present previous studies. Section 3 reviews the empirical methodology and the econometric modelling framework [fractional integration test (Geweke and Portere-Hudak, 1983), R/S analysis (Lo, 1991), and GARCH-M modelling]. In section 4 we describe the data and present the econometric results; and section 5 concludes with a summary of the main findings and implications.

2. Previous studies

Studies in the application of non-linear modelling to examine the behaviour of stock returns in the Greek market are very few. The majority of studies have primarily focused on efficiency, conditional heteroskedasticity issues and forecasting. More specifically, Papaioannou (1982, 1984) reports price dependencies in stock returns for a period of at least six days. Panas (1990) provides evidence of weak-form efficiency for ten large Greek firms. Koutmos et al. (1993) and Siriopoulos (1999) find that an exponential generalised ARCH model is an adequate representation of volatility in weekly Greek stock returns. The intertemporal relation between the US and Greek stock markets is analysed in Theodossiou et al. (1993). Siriopoulos et al. (1996) apply artificial neural networks, and compare forecasting results in the Greek and German markets. Following a different methodology based on chaotic methods, Barkoulas and Travlos (1998) try to investigate the nature of the Greek stock returns underlying process.

To our knowledge, this is the first attempt to examine volatility behaviour under time aggregation in the daily and intra-daily Greek returns series as well as the nature of shocks. Nevertheless, the list of studies in the domain of intra-daily data is actually very rich. The treatment of time in econometric modelling is very important. Irregular flow of information during a day can explain leptokurtic behaviour in financial series. We can quote Móller et al. (1990), which have studied the empirical scaling law using high frequency Foreign Exchange (hereafter FX) data. Also, Gourriıroux et al. (1999) have observed a U shaped curve for the Alcatel series volatility, in the Paris Stock Exchange. Gerhard and Hautsch (1999) have analysed seasonality in high frequency data of the futures market of bond in London, and have found that seasonalities are independent of the aggregation level. Many measures have been proposed to model daily volatility using intra-day data. Parkinson (1980) developed the PARK daily volatility estimator based entirely on high and low daily prices. Bollen and Inder (1999) proposed a generalisation of the historical volatility estimator. The above review indicates the need for additional evidence of the behaviour of stock returns in Greece using non-linear modelling.

3. Methodology

3.1 Long-memory tests

To test long-memory in both daily and intra-daily returns series, we use the fractional integration test, and more specifically the spectral regression method suggested by Geweke and Porter-Hudak (1983). We also apply the Lo rescaled range test as well as the Hurst exponent as suggested by Mandelbrot et al. (1969).

For the fractional integration coefficient d if:

- $0<d<1/2$, the process is said to exhibit long memory,
- $d = 0$, the process presents short memory,
- $-1/2<d<0$, the process exhibits intermediate memory.

Concerning the Lo rescaled range test (1991), using the values in the table of the distribution Fv, a test of the null hypothesis (short memory) may be performed at the 95 percent level of confidence by accepting or rejecting according to whether Vn is or is not contained in the interval [0.809, 1.862], which assigns equal probability to each tail. We note that Vn(q) is written as a function of q in order to underline the dependence of the modified rescaled range on the truncation lag.

3.2 GARCH(p,q)-M modelling

The GARCH-in-mean (GARCH-M) model allows for mean returns to be specified as a linear function of time-varying conditional second moments. The main advantage of this model is that it can capture the interdependence between expected returns and changing volatility. The general GARCH(p,q)-M process is presented below:

$$r_t = u_t + \delta_1 h_t^{1/2} + \varepsilon_t$$

where u_t is an exogenous vector of variables capturing past information, $\varepsilon_t \mid I_t \sim$ $N(0, h_t)$ is a zero mean serially uncorrelated random error term with a normal distribution conditional on past information,

$$h_t = \alpha_0 + \alpha_1 \varepsilon t_{-1}^{\;2} + \dots\dots\dots + \alpha_q \varepsilon_{t-q}^{\;2} + \beta_1 h_{t-1} + \dots\dots\dots + \beta_p h_{t-p}$$

is the conditional variance of the error term.

The conditional variance h_t may vary over the time as a result of :

- temporal persistence (with serial correlation up to p periods indicated by nonzero β coefficients),

- and linear dependence in the past squared innovations $\varepsilon_{t-1}^2 + \ldots\ldots\ldots + \varepsilon_{t-q}^2$ (with volatility clustering effects up to q periods indicated by nonzero α coefficients).

Engle and Bolleslev (1986) show that the persistence of shocks to volatility depends on the sum of the α_i and β_j parameters. If their sum is lower that unity, this implies a tendency for the volatility response to decay over time, at a slower rate the closer the sum is to unity. On the contrary, if the sum is equal or greater than unity, this means that volatility persists to shocks over time.

4. Data and empirical results

The behaviour of the ASE stock returns is analysed using two type of frequencies: daily and intra-daily data. More specifically, we use 8 years daily data for the period from 12/31/1990 to 12/31/1998 (2,000 observations), and 3 months intra-daily data for the period from 01/06/98 to 25/08/1998 (10,000 observations) (market opening at 10:45 a.m. and closure at 1:30 p.m.). In order to avoid non stationarity problems, we compute returns as the corresponding price changes: $r_t = \ln(X_t) - \ln(X_{t-1})$. With the aim of studying the stability of results under time aggregation, we construct different samples for daily and intra-daily series.

4.1 Unit root test and sample statistics.

Unit root test and sample statistics, for both daily (Table 1) and intra-daily (Table 2) returns series highlight the following:

- After applying the Augmented Dickey Fuller test to prices series, we see the existence of a unit root for both daily and intra-daily data. The application of the same test, this time to returns series, confirms their stationarity.
- Returns display excess kurtosis. Kurtosis falls for daily series samples between 91 and 98 as well as for intra-daily series. On the contrary, concerning the aggregated daily series between 98 and 91, we could say that they present a certain stability. Nevertheless, in all cases the null hypothesis of coefficients conforming to the normal value of three is rejected. All returns are also leptokurtic, that is, their distributions have fatter tails than a normal distribution.
- The null hypothesis of skewness coefficients conforming to the normal value of zero is always rejected at the 5 percent level. Returns display positive skewness for daily series samples (91-98) and negative for the rest.
- The hypothesis of normality is always rejected by Jarque-Bera test (J.B), confirming the results based either on skewness or on kurtosis.

4.2 ARCH LM and memory tests.

The results of the ARCH LM test, as well as the estimates of the fractional integration coefficient d, the V statistics of Lo, and the Hurst exponents are given in Tables 3 and 4 for the daily and intra-daily series respectively.

- The results obtained by using ARCH LM test show the strong presence of heteroscedasticity, which increases under time aggregation. Daily and intra-daily ASE stock returns also present in all cases a significant serial correlation. These findings imply a departure from the efficient market hypothesis, suggesting that relevant market information was only gradually reflected in stock price changes. Taking the specificity of the ASE into account the previous result can be easily interpreted. It may derive from frictions in the trading process, limited provision of information to market participants on corporate developments, market regulation, trading costs, non-synchronous trading and heterogeneous agents.
- The fractional integration test (GPH) results confirm the presence of ARCH effects only for the three first daily aggregated series (91-91, 91-92, 91-93). For the rest, long memory dominates daily series. Therefore, concerning the intra-daily series, the calculation of the d coefficient only for the 1 hour mean series is possible. The other series present non stationarities, since d is either inferior to –0.5 or superior to 0.5. This non stationarity cannot be detected by the Augmented Dickey-Fuller test. So, in intra-daily series aggregation drives to non stationarity. The major characteristics of intra-daily returns, the strong seasonal structure, as well as the high level of noise can explain a such behaviour.
- Finally, the V statistics results show the existence of short term components. Thereby, ARCH effects are detected. Nevertheless, time aggregation do not change the results, as in the case of the fractional integration test. Afterwards, Hurst exponent is not stable. For certain intra-daily aggregated returns series, it is inferior to zero. A clear signal of non stationary data.

4.3 Volatility behaviour of the intra-daily aggregated series, using the scaling law.

To study volatility behaviour of the intra-daily aggregated series we use the scaling law, given below:

$$\left|\bar{r}\left(t_i\right)\right| = \left(\frac{\Delta t_i}{\Delta T}\right)^{1/E}$$

where $\left|\bar{r}\left(t_i\right)\right|$ is the absolute value of the average return, Δt_i is the time interval over which the return is computed, ΔT is a regression constant which depends upon the ASE returns and 1/E is the drift exponent. In intra-daily series we find that the determination coefficient is equal to 0.99 and the standard errors of the exponent 1/E are less than 1%. Also, the scaling law exponent 1/E is equal to 0.93. This result permits to reject the hypothesis that the returns series follows a random walk process.

Looking at the figure 3 in appendix, we observe that volatility increases with the aggregation level, but the returns variations are not proportional. This scaling law has been associated with fractal phenomena already seen in the empirical behaviour of FX markets (Móller et al., 1997). Therefore, the intra-daily returns series are not self-similar fractals. *The sample statistics presented in the previous section show that the distributions of prices changes are increasingly leptokurtic with* *increasing time intervals and hence distinctly unstable. This fact gives more weight to the scaling law, since it is not a consequence of a stable random process.*

Volatility is calculated using the mean absolute value of the intra-daily returns. As Móller et al. (1990) and Guillaume et al. (1997) show, this definition of volatility captures better autocorrelation and seasonality in data. Figures 1-2 in appendix, present the volatility graphs of the 5 minutes series[1]. We see that when we take the last value of returns in order to compute volatility, there is no apparent structure. On the contrary, when the average returns are used, a fractal structure appears. Taking different time intervals seem not to change the structure of volatilities. We observe some peaks when the market opens and closes, while during the rest of the day, volatility is lower and more stable. Seasonality patterns seem to be independent of the aggregation level.

The results obtained previously, confirm the existence of non stationarity and seasonality in the intra-daily aggregated returns series. We need to use rigorous methods to remove seasonality and make stationary such type of data. Thus, in order to investigate the source of volatility in the Greek stock market, we prefer applying a GARCH-M model only to the daily returns series.

4.4 GARCH(p,q)-M estimation

A GARCH(p,q)-M model was estimated for the daily returns series of the ASE (2000 observations). In our application for the estimation of the GARCH-M model, we use the Berndt, Hall B.H., Hall R.E., and Hausman (1974) maximum likelihood method (henceforth BHHH). In order to start the estimation procedure, we must select a simple autoregressive specification for the u_t term based on the sequence of past stock returns. Box and Jenkins approach suggests that a simple AR(1) is a reasonable and parsimonious specification for all daily stock returns. The second step consists in examining the residuals of the AR(1) process for the presence of GARCH effects.

Since we have already verified the existence of such effects in the ASE daily returns series, we can continue to the estimation of the AR(1) process with errors that follow a GARCH(1,1)-M process. In order to explain the source of volatility in the Greek stock market, we introduce two shocks in the equation of variance:

– an endogenous shock describing the expectations of the agents about the future value of the Greek stock index, given by the following equation which is a simple feigenbaum chaotic model:

$$z_t = 3.57z_{t-1}(1-z_{t-1})$$

where z_t is a stochastic variable,

– an exogenous shock e_t ´ N(0,1).

So, with these explanations, we can write the final form of our process.

$$r_t = c + \varrho r_{t-1} + \delta_1 h_t^{1/2} + \varepsilon_t$$

[1] We obtain similar results when using the 10, 15 minutes, and 1 hour aggregated series. For this reason we only report the results concerning the 5 minutes series. The other figures are available from the authors on request.

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma_1 z_t^2 + \gamma_2 e_t^2$$

The obtained results are presented in the table 5.

The significant influence of conditional volatility on stock returns is captured by the positive estimated coefficient δ_1. Thus, the hypothesis that volatility is an important determinant of stock pricing is well confirmed. *The positive relation between risk*[2] *and return* is also proved by the obtained value of $\delta_1 = 0.208281$.

An alternative way for identifying the nature of memory in the equation of variance, is to calculate the sum of α_i and β_j. In our application this sum (0.771543+0.216198=0.987741) is very close to one, indicating a *tendency for the volatility response to shocks to display a longer memory*. The conditional variance h_t is also found to vary over time as a result of *volatility clustering effects*, confirmed by a significant α_1 (0.771543) parameter.

The study of the impact of *market forces* on stock returns, by introducing endogenous shocks in the equation of variance, constitutes a powerful tool, that gives important information about the underlying dynamics of the Greek stock market. The fact that $\gamma 1$ is significant shows the particularity of the source of high volatility in emerging markets. Endogenous changes can drive to risk exposures and market instability (for example see Kyrtsou and Terraza, 2000a,b). According to Harvey (1995) it is more likely that the emerging market returns are influenced by local than global information variables. One possible interpretation of this influence is that such markets are segmented from world capital markets.

5. Conclusion

The purpose of this paper was to investigate empirically the behaviour of volatility, the aggregation effects and the nature of shocks that influence the Athens Stock Exchange returns. To do so, we make use of daily and intra-daily data. The empirical analysis found that, ASE stock returns are characterised by a distribution departing from the normal one, and by volatility that tends to change over time and to be serially correlated. Series aggregation has also shown that under time aggregation daily returns seems to exhibit long memory, while intra-daily returns become non stationary. These findings confirm the results of empirical studies in developed Stock Exchanges. Nevertheless, even if fractality and high volatility constitute common features of emerging and developed capital markets, their source is completely different. Endogenous factors, such as local information and changes of investors expectations, play a more important role in emerging Stock Exchanges. The fact that emerging market returns are not spanned by the developed market returns, due of low correlation of emerging with developed markets, is very interesting for investors who diversify their portfolios. *Thus, including emerging market assets in a mean-variance efficient portfolio will significantly reduce portfolio volatility and increase expected returns.*

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[2] We prefer interpreting δ_1 as liquidity risk premium and not as risk premium, since we model market returns rather that excess returns.

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APPENDIX

Figure 1: *5 minutes series (mean)*

a. *Volatility behaviour of the intra-daily aggregated returns series*

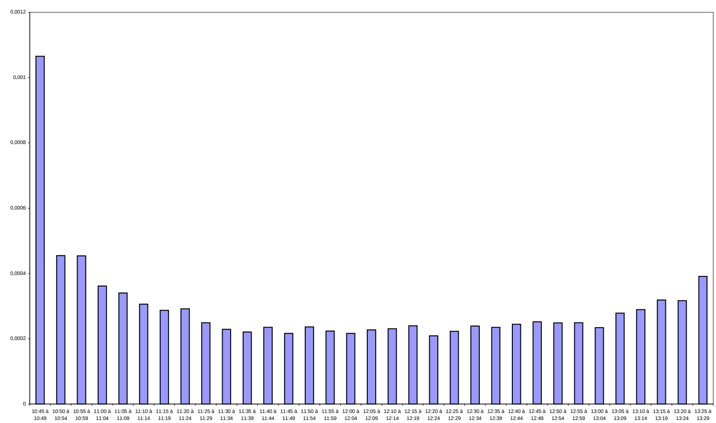


Figure 2: 5 minutes series (last value)

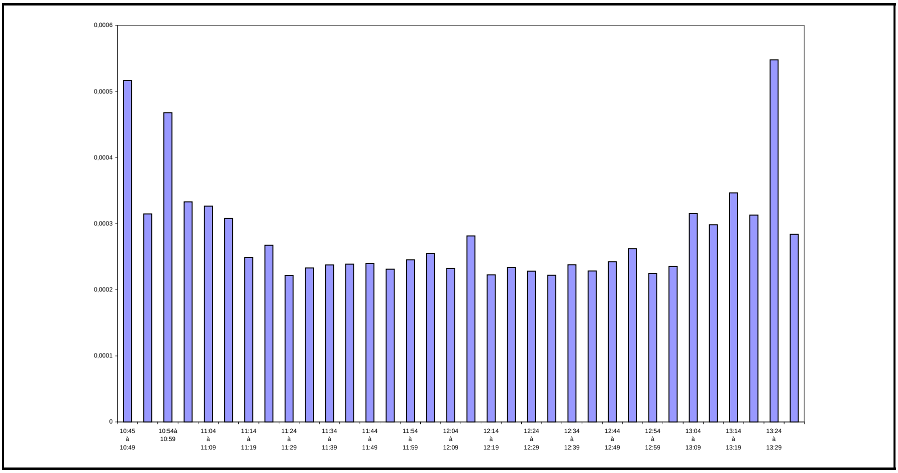
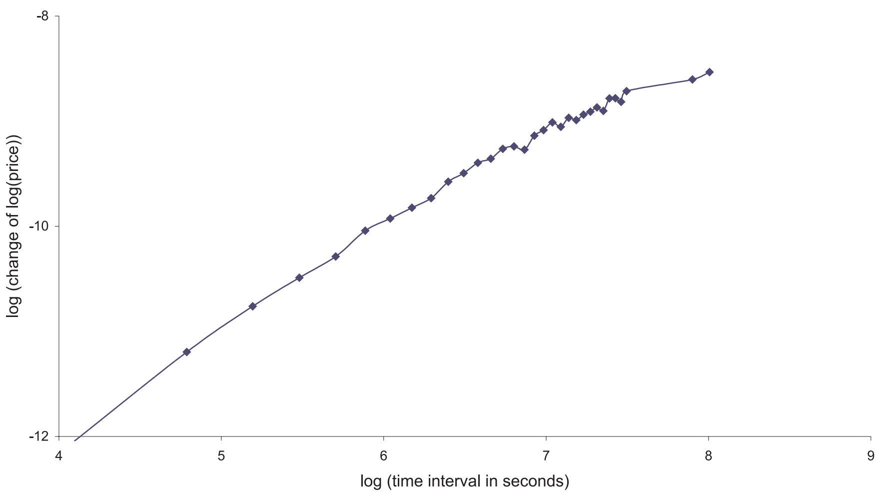


Figure 3: *The scaling law*

b. *Scaling law*



TABLES

Table 1: *Unit root test and sample statistics for the daily ASE series*

	X_t	**Returns Series $r_t = \ln(X_t / X_{t-1})$**					
Series	**Dickey Fuller**	**Dickey Fuller**	**Mean**	**Kurtosis**	**Skewness**	**J.B**	**Q(p)**
91-91	-0.8933	-5.501	-0.000247	8.31564	0.562935	303.8	33.698
91-92	-1.0166	-18.79	-0.000284	7.2148	0.505340	390.6	38.990
91-93	-1.6306	-24.46	1.63^{e}-05	6.54711	0.203857	398.9	33.623
91-94	-1.9984	-21.372	-3.04^{e}-05	6.4486	0.208794	503.3	55.155
91-95	-2.2552	-30.4515	-6.72^{e}-06	6.938703	0.254993	821.5	67.155
91-96	-2.4574	-33.28	4.59^{e}-07	7.44002	0.259257	1248	73.249
91-97	-2.5281	-34.928	0.000115	7.133212	0.089932	1246	106.05
91-98	0.9316	-37.089	0.000234	6.718896	0.017521	1152	104.75
98-98	-1.3944	-6.51636	0.001065	4.07737	-0.248702	14.73	9.521
97-98	-0.0996	-9.7307	0.000936	4.71302	-0.306032	68.80	37.726
96-98	-0.0814	-11.808	0.000636	6.11101	-0.239802	309.3	53.813
95-98	0.3373	-13.812	0.000499	6.94548	-0.154547	651.3	74.668
94-98	0.6812	-15.727	0.000365	6.84444	-0.093957	770.4	89.099
93-98	0.6662	-17.185	0.000407	6.63645	-0.139082	831.3	85.321
92-98	0.9039	-18.232	0.000302	6.45229	-0.070315	871.5	97.218
91-98	0.9316	-18.993	0.000234	6.72225	0.017536	1154	104.81

Table 2: *Unit root test and sample statistics for the intradaily ASE series*

	X_t	**Returns Series $r_t = \ln(X_t / X_{t-1})$**					
Series	**Dickey Fuller**	**Dickey Fuller**	**Mean**	**Kurtosis**	**Skewness**	**J.B**	**Q(p)**
Mean 1 min	-1.4681	-39.7	-2.55^{e}-006	385.53	-6.944	>>>[3]	369.26
Mean 5 min	-1.3186	-20.4378	-1.47^{e}-05	74.5818	-1.70445	>>>	165.94
LastValue 5 min	-1.3062	-20.8219	-1.48^{e}-05	61.07428	-1.19301	>>>	59.367
Mean 10 min	-1.2705	-12.9078	-2.94^{e}-05	36.68875	-1.672372	>>>	73.207
LastValue 10 min	-1.2817	-13.6848	-2.94^{e}-05	22.02669	-0.393360	>>>	50.393
Mean 15 min	-1.3634	-10.5871	-4.35^{e}-05	25.89016	-1.35859	>>>	48.627
LastValue 15 min	-1.3555	-10.4865	-4.21^{e}-05	10.938	-0.004678	>>>	41.775
Mean 1hour	-1.5816	-5.2178	-9.62^{e}-05	6.574173	-0.14434	96.97	9.68
LastValue 1 hour	-1.6297	-4.6063	-0.000121	7.51672	-0.485027	160.9	33.209

[3] Value superior to 10.000.

Table 3: *Long and short memory tests for the daily ASE returns series*

Series	ARCH LM	GPH	V stat. Lo	Hurst[4] Exponent
91-91	7.714	D = 0	1.2768	0.392
91-92	29.28	D = 0	1.3380	0.376
91-93	41.07	D = 0	1.6815	0.551
91-94	53.13	D > 0	1.4180	0.503
91-95	88.28	D > 0	1.3909	0.490
91-96	110.27	D>0	1.3659	0.476
91-97	122.43	D >0	1.3447	0.482
91-98	165.16	D >0	1.3259	0.484
98-98	10.1095	D >0	1.5258	0.371
97-98	26.4264	D =0	1.2863	0.160
96-98	44.0507	D >0	0.9885	0.338
95-98	85.543	D >0	1.1026	0.399
94-98	119.798	D >0	1.3241	0.504
93-98	128.467	D >0	1.330	0.513
92-98	141.911	D >0	1.2282	0.442
91-98	157.30	D >0	1.3636	0.496

Table 4: *Long and short memory tests for the intra-daily ASE returns series*

Series	ARCH LM	GPH	V stat. Lo	Hurst Exponent
Mean 1 min	24.24	D =0	1.320	0.551
Mean 5 min	181.57[5]	##	1.1559	<u>-0.196</u>[6]
LastValue 5 min	21.7007	##	1.1188	<u>-1.365</u>
Mean 10 min	6.32749	##	1.6315	<u>-1.523</u>
LastValue 10 min	5.45803	##	1.2611	0.219
Mean 15 min	6.08706	##	1.3847	0.778
LastValue 15 min	85.798[7]	##	1.0208	<u>-0.152</u>
Mean 1hour	---	##[8]	1.9144	0.341
LastValue 1 hour	46.77	##	1.9225	0.085

---

4 The process is a random walk when H = 0.5, mean-reverting when $H \in (0, 0.5)$, mean-averting when $H \in (0.5, 1)$.

5 for k = 33.

6 When $H \notin (0,1)$, the series is not stationary.

7 for k = 11

8 If d > 0,5 or < -0,5, the series is not stationary.

Table 5: *Estimates for AR(1)-GARCH(1,1)-Model for the daily ASE returns*

Coefficient	**Value**	**t-Statistics**	
Mean equation	c	0.001426	4.779617*
	ϱ	0.135920	4.476878*
	δ_1	0.208281	3.747857*
Variance equation	α_0	0.000014	3.716312*
	α_1	0.771543	31.43214*
	β_1	0.216198	7.138159*
	γ_1	0.0000108	6.118139*
	γ_2	0.00000023	1.101621

*significant coefficient at 5%