DOES TRADING VOLUME INFLUENCE GARCH EFFECTS? – SOME EVIDENCE FROM THE GREEK MARKET WITH SPECIAL REFERENCE TO BANKING SECTOR

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Abstract

This paper examines whether trading volume has any impact on GARCH and GJR-GARCH estimates for the Greek banking sector and the Greek FTSE/ASE Mid 40 stock price index for the period of 2000-2005. The results from the GARCH and GJR-GARCH models with and without volume indicate that GARCH and GJR-GARCH effects become smaller when trading volume is taken into account. In particular, these effects are seen mainly through the influence on the past conditional volatility coefficient in both the models that include trading volume. However, the coefficient of squared innovations improves after the inclusion of trading volume. This means that there still remains unexplained information in the market that it is not captured through the modelling approach used. The results suggest that trading volume partly affects the GARCH and GJR-GARCH estimates implying a negative relationship between stock price volatility and trading volume. It is also found that bad news can have a significant impact on stock price volatility.

Key words: Volatility clustering, GARCH models, Greek Banking Sector, Athens Stock Exchange.

JEL Classification: G15.

1. Introduction

A number of studies bring to light empirical evidence on 'volatility clustering' with regard to the impact of the news on stock price volatility. Seminal studies finding evidence on 'volatility clustering' are provided by Engle (1982), Pindyck (1986), French et al. (1987), Poterba and Summers (1986) and Bollerslev (1986). All of these studies support the view that news tends to be clustered together and this has an influence on stock price volatility. More recently, Friedman and Sanddorf-Kohle (2002) analyzed volatility dynamics in the Chinese stock markets comparing the EGARCH with the asymmetric model proposed by Glosten, Jagannathan, and Runkle (1993), known as the GJR-GARCH model. Their empirical results find that the dynamics of the Chinese market are best represented by the GJR-GARCH model, a finding that confirms Engle and Ng's (1993) assertion that asymmetric GARCH models similar to that proposed by Glosten, Jagannathan, and Runkle (1993) are superior for estimating stock market dynamics.

Another strand of the literature examines whether trading volumes have any effect on GARCH estimates of stock market volatility. For instance, Lamoureux and Lastrapes (1990) found that GARCH estimates vanish when trading volumes are taken into account. Studies that examine similar relationships include those of Omran and McKenzie (1995) for the UK and by Sharma, Mougoue and Kamath (1996) on the US market (NYSE). The former found that autocorrelation of the squared innovations still exhibits a highly significant pattern in the UK market after the inclusion of trading volume in their GARCH estimates. The latter also noted that GARCH effects did not completely vanish in the US market when they control for trading volume.

The aim of this paper is to extend the aforementioned analysis by examining the impact of trading volume using both GARCH and the asymmetric GARCH approach suggested by Glosten, Jagannathan, and Runkle (1993). The empirical analysis is conducted on data from the Greek stock market, details of which are outlined in the following section.

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2. Data and Methodology

This paper compares the performance of GARCH and GJR-GARCH models fitted to the daily Greek banks' stock price returns and the Greek FTSE/ASE Mid 40 stock price index. We focus our attention on the Greek banking sector comprising twelve banks' stocks trading in the Athens Stock Exchange due to data availability and the liquidity of such stocks. However, bank stocks account for eleven of the twenty stocks of the Greek FTSE/ASE 20, an index that includes the first twenty stocks in market value. Due to the over-representation of bank stocks in the Greek FTSE/ASE 20 we need to choose a more representative and "independent" index excluding the over-emphasis of banks in order to compare the impact of volume on the volatility of stock price returns. For this we take the Greek FTSE/ASE Mid 40 index that comprises the forty stocks in market value after the FTSE/ASE 20. The FTSE/ASE Mid 40 is an index for medium-sized firms, consisting of 39 stocks from various industry sectors and only one from the banking sector. This allows us to compare the impact of volume on the volatility of stock price returns in the banking sector and also on an index that is not unduly influenced by banks' stocks.

Daily data on stock price returns (R) and trading volume (TV) for both the banking sector and for the FTSE/ASE Mid 40 index were obtained from the Information Dissemination Department of the Athens Stock Exchange and Globalsoft over the period of 2000-2005. The data for stock price returns have been transformed into natural logarithm applying the formula: Ln (P_t / P_{t-1}), while the data for trading volume is actual.

The GARCH model of Bollerslev (1986) provides a flexible and parsimonious approximation to conditional variance dynamics. The GARCH (1, 1) model for the conditional variance of the innovations ε_t, $\sigma_t^2 = \mathrm{var}(\varepsilon_t \mid \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots)$ is given by the following equations:

$$\varepsilon_t = u_t \sqrt{\sigma_t^2}\ ,\ u_t \text{ i.i.d. with } \mathrm{E}(u_t) = 0 \text{, and } \mathrm{E}(u_t^2) = 1, \tag{1}$$

$$R_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i R_{t-i} + \varepsilon_t\,, \tag{2}$$

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2\,, \tag{3}$$

and

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \gamma_1 TV\,. \tag{4}$$

The parameter restrictions $\beta_0 > 0$, $\beta_1 \geq 0$, $\beta_2 \geq 0$ and $\beta_1 + \beta_2 < 1$ ensure that the stochastic process $\{\varepsilon_t\}$ is well-defined (i.e., $\sigma_t^2 > 0 \forall t$) and covariance stationary with $\mathrm{E}(\varepsilon_t) = 0$, Var($\varepsilon_t$)=$\sigma^2$, Cov ($\varepsilon_t, \varepsilon_s$)=0 $t \neq s$.

In many studies the GARCH (1, 1) process has been successfully applied to capture volatility clustering in financial data. In the simple GARCH (1, 1) approach bad and good news, i.e., negative and positive shocks, have the same impact on the conditional variance. This feature of GARCH models does not correspond to the results of a number of researchers, who have found evidence of asymmetry in stock price behaviour. Particularly, negative surprises seem to increase volatility more than positive surprises. To allow asymmetric volatility effects, Glosten, Jagannathan and Runkle (1993) add an additional term in the conditional variance Equation (3):

$$R_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i R_{t-i} + \varepsilon_t\,, \tag{5}$$

$$\sigma_t^2 = \beta_0 + \beta_1 (1 - \beta_2 \mathrm{I}_{t-1}) \varepsilon_{t-1}^2 + \beta_3 \sigma_{t-1}^2\,, \tag{6}$$

and

$$\sigma_t^2 = \beta_0 + \beta_1 (1 - \beta_2 \mathrm{I}_{t-1}) \varepsilon_{t-1}^2 + \beta_3 \sigma_{t-1}^2 + \gamma_1 TV\,. \tag{7}$$

Here, $\mathrm{I}_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and $\mathrm{I}_{t-1} = 0$ If $\varepsilon_{t-1} \geq 0$.

This is an asymmetric GARCH model which we denote as GJR-GARCH (1, 1) after Glosten, Jagannathan, and Runkle (1993). The process is well-defined if the conditions $\beta_0 > 0$, $\beta_1 \geq 0$, $\beta_1(1-\beta_2) \geq 0$ and $\beta_3 \geq 0$ are satisfied.

3. Empirical Results

Tables 1 and 2 provide preliminary statistics for the stock price returns and trading volume variables of the Greek banking sector and the Greek FTSE/ASE Mid 40 stock price index. Table 1 shows that the mean for the stock price returns of the banking sector and stock price index is negative and equal to -0.079% and -0.15% respectively, while the mean for daily trading volume is equal to 127,020.86 Euros and 2,190,684.72, Euros respectively. Bank stock price returns and trading volume are, therefore, both lower than that of the FTSE/ASE Mid 40 stock index. There is also kurtosis in the return series under investigation suggesting fat tails and this supports the use of GARCH modelling approaches to investigate market dynamics.

Table 1

Descriptive Statistics of the Greek banking sector and the Greek FTSE/ASE Mid 40 stock price index: 2000-2005

	Banking Sector Returns	Banking Sector Volume (in Euros)	FTSE/ASE Mid 40 Returns	FTSE/ASE Mid 40 Volume (in Euros)
Mean	-0.00079	127,020.86	-0.0015	2,190,684.72
St. Dev.	0.018	157,978.44	0.020	2,570,436.41
Skewness	0.12	9.68	-0.20	5.74
Kurtosis	4.038	129.25	2.92	53.60

Table 2 shows that there is strong serial correlation in the banking sector return series and the FTSE/ASE Mid 40 stock price index when we consider daily 8, 16 and 24 lags, respectively This suggests that the methodology should adopt a model that is best suited to capture this feature. As mentioned above, we use the GARCH and the GJR-GARCH models to analyse the impact of trading volume on the stock price volatility of the banking sector and the FTSE/ASE Mid 40 stock price index.

Table 2

Serial Correlation of the Greek banking sector returns and the Greek FTSE/ASE Mid 40 stock price index: 2000-2005

	Banking Sector Returns	FTSE/ASE Mid 40 Returns
LB(8)	31.58*	46.97*
LB(16)	45.56*	65.63*
LB(24)	63.05*	104.92*

Note: * shows significance at the 5% level. LB is the Ljung Box statistic with daily 8, 16 and 24 lags.

The impact of trading volume on GARCH and GJR-GARCH estimates is tested for the Greek banking sector and the Greek FTSE/ASE Mid 40 stock price index, following Lamoureux and Lastrapes (1990). Using GARCH estimates, Table 3 shows that the impact of trading volume on volatility in the Greek banking sector is not significant at the 5% level. In particular, we find that the relationship between trading volume and volatility of stock price returns in the Greek banking sector is negative and equal to -1.11. This means that a 1% change in trading volume will decrease the coefficient of volatility by 1.11%. In addition, a comparison of the GARCH coefficients without and with volume reveals that the past conditional volatility coefficient (β_1) has reduced from 0.69 to 0.030 after the inclusion of trading volume in the GARCH model. This finding is in accordance with Lamoureux and Lastrapes (1990) who found that GARCH estimates deteriorate when trading volume is added into such models. In contrast to this finding, the coefficient of squared innovation (β_2) has been increased from 0.21 to 0.58 after the inclusion of trading volume in the GARCH model. Overall, the results in Table 3 reveal that the inclusion of trading volume in the GARCH model partly reduces the GARCH effects for the banking sector stock price returns. Similar results are also observed for the FTSE/ASE Mid 40 stock price index.

Table 3

GARCH estimates of the Greek banking sector and the Greek FTSE/ASE Mid 40 stock price index: 2000-2005

	Banking Sector Returns		FTSE/ASE Mid 40 Returns	
Variables	Without Volume	With Volume	Without Volume	With Volume
Return Coefficients				
α_0	-0.00072 (0.00056)	-0.00069 (0.00056)	-0.0013* (0.0006)	-0.0014* (0.00060)
α_1	0.18* (0.032)	0.18* (0.032)	0.20* (0.032)	0.20* (0.032)
α_2	-0.070* (0.032)	-0.069* (0.054)	-0.093* (0.032)	-0.093* (0.032)
α_3	0.055** (0.032)	0.054** (0.032)	N.A.	N.A.
GARCH Coefficients				
β_0	3.42* (6.18)	2.62* (1.33)	5.40* (2.09)	3.14* (2.57)
β_1	0.69* (0.03)	0.030* (0.011)	0.87* (0.016)	0.052* (0.023)
β_2	0.21* (0.023)	0.58* (0.090)	0.12* (0.016)	0.49* (0.11)
TV	N.A.	-1.11 (1.38)	N.A.	7.96 (9.35)
Log-Likelihood	3588.95	3513.57	3544.79	3441.12

Note: *shows significance at the 5% level. ** shows significance at the 10% level. The Akaike criterion is used to identify the number of lags in the return equation.

Table 4 presents the results from the GJR-GARCH (1, 1) model with and without trading volume for the Greek banking sector and the Greek FTSE/ASE Mid 40 stock price index. For the banking sector stock price returns, the GJR-GARCH coefficients without and with volume reveal that the past conditional volatility coefficient (β_1) has reduced from 0.71 to 0.24 after the inclusion of trading volume in the GJR-GARCH model. Similar results are obtained for the FTSE/ASE Mid 40 stock price index, that is, the coefficient (β_1) has reduced from 0.89 to 0.24 after the inclusion of trading volume. In contrast, the coefficient of squared innovation (β_2) increases from 0.16 to 0.47, for the banking sector stock price returns and from 0.056 to 0.47 for the FTSE/ASE Mid 40 stock price index, after the inclusion of trading volume. Similar increases are obtained for both the banking sector stock price returns and the FTSE/ASE Mid 40 stock price index when we include the additional coefficient (β_3) that captures asymmetric volatility effects. In particular, the relationship of the impact of bad news on banking sector returns and FTSE/ASE Mid 40 stock price index is found to be negative (-0.57 and -1.66, respectively) without the inclusion of volume in the GJR-GARCH (1, 1) model and positive with the inclusion of volume (0.71 and 0.71, respectively). This means that the GJR-GARCH estimates do not deteriorate when the coefficients of the bad news for the Greek banking sector and the Greek FTSE/ASE Mid 40 stock price index are concerned. In addition, the impact of bad news is found to increase with the inclusion of trading volume.

Table 4

GJR-GARCH estimates of the Greek banking sector
and the Greek FTSE/ASE Mid 40 stock price index: 2000-2005

	Banking Sector Returns		FTSE/ASE Mid 40 Returns	
Variables	Without Volume	With Volume	Without Volume	With Volume
Return Coefficients				
α_0	-0.00072 (0.00056)	-0.00069 (0.00056)	-0.0013* (0.00060)	-0.0013* (0.00060)
α_1	0.18* (0.032)	0.18* (0.032)	0.20* (0.032)	0.20* (0.032)
α_2	-0.070* (0.032)	-0.069* (0.054)	-0.093* (0.032)	-0.093* (0.032)
α_3	0.055** (0.032)	0.054** (0.032)	N.A.	N.A.
CJR-GARCH Coefficients				
β_0	2.85* (5.36)	3.91* (3.092)	0.0000045* (0.0000017)	4.46* (6.94)
β_1	0.71* (0.028)	0.24* (0.074)	0.89* (0.014)	0.24* (0.11)
β_2	0.16* (0.022)	0.47* (0.13)	0.056* (0.015)	0.47* (0.19)
β_3	-0.57* (0.24)	0.71* (0.12)	-1.66* (0.61)	0.71* (0.14)
TV	N.A.	-1.98 (1.45)	N.A.	-1.71 (9.54)
Log-Likelihood	3584.89	3439.55	3549.88	3363.41

Note: *shows significance at the 5% level. ** shows significance at the 10% level. N.A. means not available. The AKAIKE criterion is used to identify the number of lags in the return equation.

4. Concluding remarks

This paper examines whether trading volume has any impact on GARCH and GJR-GARCH estimates for the Greek banking sector and the Greek FTSE/ASE Mid 40 stock price index. Overall, the results from the GARCH and GJR-GARCH models with and without volume indicate that GARCH and GJR-GARCH effects become smaller when trading volume is taken into account. In particular, these effects are seen mainly through the influence on the past conditional volatility coefficient in both the models that include trading volume. However, the coefficient of squared innovations improves after the inclusion of trading volume. This means that there still remains unexplained information in the market that it is not captured through the modelling approach used. Our results, therefore, partly concur with the findings of Lamoureux and Lastrapes (1990) who find that trading volume reduces GARCH effects although it seems that these effects are smaller when asymmetric GARCH models such as GJR-GARCH are used to model such relationships. An interesting possible area for future research would be to use asymmetric models with long memory (see Hwang, 2001; and Ruiz and Perez, 2003) to further examine the impact of trading volume on stock price volatility.

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