Chapter VII

Event-induced Volatility in Thinly Traded Markets: Controlling for Non-Synchronous Trading and Volatility Clustering

Abstract.

This paper investigates non-synchronous trading and non-trading effects as well as volatility clustering in asset returns during event and non-event periods in the Norwegian relatively thinly traded equity market. The main objective is to find any periodic differences during events in conditional mean and volatility characteristics, which suggest a need for more elaborate methodologies for abnormal return and statistical test calculations in classical event studies. We employ ARMA-GARCH lag specifications for the conditional mean and volatility based on return series containing equal-weighted asset returns from firms either classified in event or non-event periods. The Bayes Information Criterion (BIC) preferred ARMA lag specification models the non-synchronous trading and non-trading effects while the BIC preferred GARCH lag specification models volatility clustering. We employ elaborate specification test statistics to report any model misspecification. The empirical specifications show significant ARMA coefficients suggesting non-synchronous trading and non-trading in the conditional mean. The GARCH specification is strongly significant suggesting volatility clustering. The elaborate specification test statistics reject misspecification from the BIC preferred ARMA-GARCH residuals. The empirical results for univariate and bivariate specifications suggest that the conditional volatility increases strongly in event periods relative to non-event periods. The increase in conditional volatility is strongest for event periods most closely centred on the announcement date. A heteroscedastic volatility specification is therefore strongly warranted. Consequently, our results suggest that non-synchronous trading and volatility clustering may have considerable influence on inferences in classical event studies. We therefore advocate a model for abnormal return and test statistic calculations in classical event studies, which controls for non-synchronous trading and volatility clustering.

Classification:

Keywords: Event studies, ARMA-GARCH, Non-synchronous trading, Volatility Clustering

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1 Introduction

The main purpose of the paper is to show the need to control for event-induced volatility in classical event studies (volatility clustering). Many authors have identified the hazards of ignoring event-induced volatility. Employing (G)ARCH methodology[1] for the conditional volatility process we can control for conditional heteroscedasticity and changing volatility. This investigation aims to show that classical events cause strong increase in the conditional volatility applying ARMA-GARCH specifications. The ARMA-GARCH specifications control for non-synchronous trading and volatility clustering and should produce residuals that are unconditional homoscedastic. Boehmer et al. (1991) warns of event induced volatility in event studies and suggests a simple adjustment to the OLS test statistics. Moreover, for the ARMA-GARCH maximum-likelihood estimation the model produces residuals that are unconditional homoscedastic and therefore unadjusted abnormal return test statistics can be employed. Hence, if we find a strong event volatility increase relative to non-event volatility, the ARMA-GARCH methodology is strongly justified.

This paper does not investigate the cause of event-induced volatility[2] but rather show the need to control for changing volatility. We employ a sample of mergers and acquisitions in the Norwegian thinly traded equity market. To determine the level of the volatility in event and non-event periods we form return series employing the event and non-event period firm samples. Event series are formed from event period firms in three different event windows. Non-event series are formed from non-event period firms where the return series are all collected from periods outside the largest event window. Our objective is to establish the mean and volatility characteristics for all these event and non-event series. The time series models must contain several elaborate features to avoid misspecification.

Firstly, in thinly traded markets non-synchronous trading may produce serious biases in the moments and co-moments and therefore may produce spurious relationships (Campbell, 1997 and Solibakke, 2000a, 2000b). To control for non-synchronous trading we employ an ARMA(p,q) lag specification in the conditional mean. The lag specifications for p and q are the BIC preferred (Schwarz, 1978) model. Secondly, the volatility of all event and non-event portfolios is specified employing (G)ARCH formulations, to control for volatility clustering and changing volatility. The conditional volatility are modelled applying a BIC preferred ARMA (m,n) lag specification for squared residuals from the conditional mean specification. The volatility series are therefore readily available from the estimations. Thirdly, asymmetric volatility is modelled as shown by Glosten et al. (1993) and Nelson (1991). Finally, leptokurtosis is found in the Norwegian equity market as in all other international equity markets. Hence, we employ a univariate ARMA-GARCH lag specification with student t-

[1] An alternative methodology is Semi-Non-Parametric (Gallant & Tauchen, 1989, 1991).
[2] Brown et al. (1988,1989)

density distributions (Bollerslev 1986/87) and bivariate GARCH-in-Mean models (Engle & Kroner, 1995) with multi-normal distributions.

Our specification tests show that both the univariate and bivariate ARMA-GARCH models filters all non-synchronous trading and volatility clustering in event and non-event periods. Hence, as our results suggest no data dependence in the return series, we can report no model misspecification. Moreover, if this result maintains its validity into the market model we have obtained a sounder basis for abnormal return calculations in event-studies employing unadjusted test statistics.

The investigation reports a strongly higher conditional volatility in event periods relative to non-event periods for both selling and acquiring firms. Therefore the investigation proposes new models for classical event studies in the future.

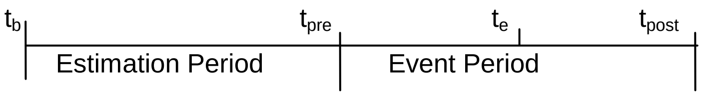
This paper extends previous works in several areas. Firstly, the increase in conditional volatility from non-event to event periods is measured employing both univariate and bivariate subordinated stochastic volatility specifications (Clark, 1973, Epps and Epps, 1976, Tauchen and Pitts, 1983). The bivariate ARMA-GARCH model is employed to better specify market dynamics and cross-autocorrelation in mean and volatility. Secondly, the leptokurtosis in distributions often found in stock markets are considered using student-t density log-likelihood functions. Thirdly, we employ asymmetric conditional volatility parameters for all estimations. Fourthly, elaborate specification tests are employed for model misspecification. Finally, we propose a new event-study methodology controlling for non-synchronous trading and volatility clustering employing the market model in classical event studies.

The remainder of the article is organised as follows. Section 2 defines the event periods, describes the equal-weighted series approach in event and non-event periods and defines the conditional mean and volatility equations from the family of ARMA-GARCH lag specification models. Section 3 describes the empirical data and the time series adjustment procedures. Section 4 reports the univariate results from the analysis. Section 5 reports the bivariate estimation results. Section 6 investigates the significance of the conditional volatility increase applying likelihood ratio tests. As Section 6 report significant changes, Section 7 suggests two time-series specifications for classical event studies. Finally Section 7 summarises our findings.

2 Definitions and Methodology

2.1 The Event Period

In event studies, the objective is to examine the market's response through the observation of security prices around such events. For merger and acquisitions[3] it is related to the release of information to market participants through the financial press. Normal or predicted returns for an asset are those returns that are expected if no event occurs. The time line for a typical event study for a mergers and acquisitions case may be represented as follows



where t_b is the first period used in the estimation of a normal security return; t_{pre} is the first period used in the calculation of abnormal returns; t_e is the event date; and t_{post} is the last period used in the calculation of abnormal returns. In the literature we usually find a selection of t_{pre} equal to -40 days and t_{post} equal to + 40 days relative to t_e (day 0). Hence, the event period will in this case consist of 80 days. Our study applies also narrower event periods. We define event periods of t_{pre} equal to -20 (-10) days and t_{post} equal to + 5 (+1) days relative to t_e (day 0). Note that the length of the estimation period is not relevant for this portfolio study. However, in a classical event study the length of the estimation period is an important decision to make.

2.2 Event and Non-Event Return Series

To study any change in return and volatility characteristics from non-event to event series we form equally weighted portfolios from firm return series classified in event periods and non-event periods. The classification of an event period follows the definitions of t_{pre} and t_{post} in section 2.1. All firms that by definition are categorized into a specific event period are included in the sample and the returns are averaged over the whole sample for each day relative to t_e. These calculations for portfolio returns becomes $PR_{c,t} = \frac{1}{N_{c,t}} \cdot \sum_{i=1}^{N_{c,t}} R_{c,t,i}$ where $R_{c,t,i}$ is the continuously compounded return for portfolio c, day t, asset i . $PR_{c,t}$ is portfolio c's return at date t. $N_{c,t}$ is the number of assets in portfolio c at date t.

Note that the number of firms $N_{c,t}$ may change over time in especially the event series. Therefore, a possible and permissible value for $N_{c,t}$ is zero. The time series will set these dates to missing observations.

The definition of non-event series follows this procedure. Firstly, we find the average number of firms over all event dates for the widest event window {-40,+40} days relative to t_e and employ this number of assets for the non-event series. The returns are calculated as above using a random sample of firms for the non-event sample. Return series characteristics are reported in Section 4 below.

Finally, note that model specification assumes an ergodic and stationary return series. An ergodic return series suggest that the sample moments for finite stretches of the realisation approach their population counterparts as the length of the realisation becomes infinite. A stationary time series mean that the process is in a particular state of “statistical equilibrium” (Box and Jenkins, 1976). Strict stationary is obtained if its properties are unaffected by a change in time origin. In Section 3 we will apply a special adjustment procedures to secure ergodic and stationary returns for all employed series.

2.3 The Conditional Mean and Volatility Specifications

We will apply the ARMA-GARCH specification for estimation of the mean and volatility equations. The methodology applies conditional models where non-synchronous trading may be modelled in the conditional means and volatility clustering may be modelled in the conditional volatility. The ARMA methodology may be studied in detail in Mills (1990), while (G)ARCH specifications may be studied in Engle (1982) and Bollerslev (1986, 1987). In the international finance literature we find a high number of papers with origin from these pioneer works. For a small sample we refer to Bollerslev et al. (1987,1992), Engle et al. (1986, 1995), Nelson (1991) og deLima (1995a, 1995b). Moreover, Glosten et al. (1993) extended the GARCH model to truncated GARCH to account for the leverage effects. The ARMA-GARCH methodology may be univariate og multivariate. As event studies apply the market model to specify normal returns the multivariate model may be more relevant than the univariate model.

[3] For an OLS study of abnormal returns in Norway see Eckbo and Solibakke, 1992. For an international review Eckbo, 1987.

2.3.1 The univariate and asymmetric ARMA-GARCH-in-Mean specification

The general asymmetric ARMA(*p,q*) - GARCH(*m,n*) -in-Mean specification of the conditional mean and volatility can be defined as follows:

$$R_{j,t} = \phi_{j,0} + \sum_{i=1}^{p} \phi_{j,i} \cdot R_{j,t-i} + \delta_j \cdot h_{j,t}^{\frac{1}{2}} + \varepsilon_{j,t} - \sum_{i=1}^{q} \theta_{j,i} \cdot \varepsilon_{j,t-i} \quad (1)$$

$$\lambda_{j,i,t} = \gamma_{j,i} \quad \text{if and only if} \quad \varepsilon_{j,t-i} < 0 \quad (2)$$

$$E(\varepsilon_{j,t}^2 \mid \Phi_{j,t-i}) = h_{j,t} = m_{j,0} + \sum_{i=1}^{m} (a_{j,i} + \lambda_{j,i,t}) \cdot \varepsilon_{j,t-i}^2 + \sum_{i=1}^{n} b_{j,i} \cdot h_{j,t-i} \quad (3)$$

where $R_{j,t}$ is the portfolio *j's* return in period *t*; $\varepsilon_{j,t}$ is a random variable (residual) distributed as either normal $N(0,\sigma^2)$ or student-t $D(0,\sigma^2,\omega)$ where ω is the degree of freedom; $\theta_{I,j}$ is lag *i* for the moving average or non-synchronous trading parameters of portfolio *j* in the conditional mean equation (1); $\lambda_{j,i,t}$ measures the leverage effect, $m_{j,0}$ is the constant term for portfolio *j* in the conditional volatility equation; $a_{j,i}$ is lag *i* for auto-regressive parameters for shocks of portfolio *j*; and $b_{j,i}$ is lag *i* for the conditional volatility parameters of portfolio *j*. The lag lengths *p*, *q*, *m* and *n* are determined by the BIC criterion (Schwarz, 1978) for all series.

Linear models have constant conditional volatility whatever the information of observed returns. In our approach the conditional volatility may vary but the unconditional volatility is constant. Hence, the equations above lead naturally to the consideration of non-linear stochastic processes and the (G)ARCH-in-Mean model[4] (Engle, Lillien and Robbins (1987)) show a departure from white noise. Specifically, in our model we allow the serially correlated errors to be modelled as a moving average (*MA(q))* process to capture the effect of non-synchronous trading, while the innovations $\varepsilon_{j,t}$ can be assumed to follow either a conditional normal - or a conditional student-t distribution. The conditional volatility enters the mean equation (in-Mean). Estimation usually applies the BHHH (1974) algorithm.

2.3.2 The bivariate and asymmetric ARMA-GARCH-in-Mean specification

As event studies apply the market model and therefore an overall market index to calculate normal returns, the univariate ARMA-GARCH models may not count for total market dynamics. Moreover, the index series may also contain non-synchronous trading and volatility clustering. Hence, to control for these market structure effects we employ a bivariate specification between return series and the overall index series. We employ a value-weighted index as a proxy for the market portfolio.

[4] For applications see Bollerslev, Chou, Kroner, 1992.

To model this bivariate specification we apply the MGARCH model. The Multivariate GARCH-in-Mean model (BEKK-formulation)[5] is defined as (in vector format)

$$\boldsymbol{R_t} = \boldsymbol{\phi_0} + \boldsymbol{\phi_1} \cdot \boldsymbol{R_{t-1}} + \boldsymbol{\Delta} \cdot vech(\boldsymbol{H_t}) + \boldsymbol{\varepsilon_t} - \boldsymbol{\theta_1} \cdot \boldsymbol{\varepsilon_{t-1}} \quad (5)$$

$$\boldsymbol{H}_t = \boldsymbol{m}' \cdot \boldsymbol{m} + \boldsymbol{A}_1' \cdot \boldsymbol{\varepsilon_{t-1}} \cdot \boldsymbol{\varepsilon}_{t-1}' \cdot \boldsymbol{A_1} + \boldsymbol{B}_1' \cdot \boldsymbol{H}_{t-1} \cdot \boldsymbol{B_1} \quad (6)$$

where $\varepsilon_t \,|\Omega_{t-1} \sim N(0,\boldsymbol{H_t})$ and *vech* $(\boldsymbol{H_t})$ is the column stacking operator of the lower portion of a symmetric matrix, $R_t = \begin{pmatrix} R_{i,t} \\ R_{M,t} \end{pmatrix}, \varepsilon_t = \begin{pmatrix} \varepsilon_{it} \\ \varepsilon_{Mt} \end{pmatrix}, \Delta = \begin{pmatrix} \delta_{11} & \delta_{1M} & \delta_{13} \\ \delta_{21} & 0 & \delta_{MM} \end{pmatrix}$, where $\boldsymbol{\mu}$ is 2 x 1 vector of constants in the conditional mean. $\boldsymbol{m}$, $\boldsymbol{A_1}$, $\boldsymbol{B_1}$ are 2 x 2 parameter matrices, and the elements of the conditional volatility matrix $\boldsymbol{H_t}$ are $h_{i,t} = var_t(R_{i,t})$, $h_{i,M,t} = cov_t(R_{i,t}, R_{M,t})$, and $h_{M,t} = var_t(R_{M,t})$. The θ_1 parameter specifies non-synchronous trading in the bivariate system of mean equations. The δ_{11} is the ARCH-in-Mean parameter in the equation of $R_{i,t}$ that corresponds to $h_{i,t}$, δ_{1M} is the ARCH-in-Mean parameter in the equation of $R_{i,t}$ that corresponds to $h_{i,M,t}$ and δ_{13} is the ARCH-in-Mean parameter in the equation of $R_{i,t}$ that corresponds to $h_{M,t}$. δ_{21} is the ARCH-in-Mean parameter in the equation of $R_{M,t}$ that corresponds to $h_{i,t}$, and δ_{MM} is the ARCH-in-Mean parameter in the equation of $R_{M,t}$ that corresponds to $h_{M,t}$. Note that the conditional volatility specification for $\boldsymbol{H_t}$ in (6) guarantees the positive definiteness of $\boldsymbol{H_t}$ and allows feedback between the volatility of the individual portfolio and the market. **m** is a lower triangular matrix. Finally, we extend this model to measure asymmetric volatility applying the GJR methodology (Glosten et al., 1993) in the bivariate estimation. Hence, we extend the above model by the parameters γ_1 for asymmetry in the portfolio and γ_2 for asymmetry in the market index. Note that this bivariate ARMA(1,1)-GARCH(1,1) can be extended to any lag lengths *p, q*, *m* and *n* as specified for univariate specifications. The Bayes Information Criterion (BIC) is applied for both ARMA (mean) and GARCH (volatility) lag specifications. As for univariate GARCH estimations, the BHHH (1974) algorithm is applied for estimation.

3 Empirical Data sources and Time Series Adjustments

The study uses daily continuously compounded returns ($\ln \frac{P_t}{P_{t-1}}$) of individual Norwegian stocks spanning the period from October 1983 to February 1994. The logarithmic returns are scaled by one hundred to avoid any scaling problems during estimation. Data are obtained from Oslo Stock Exchange Information A/S. The data includes the crash period of October

[5] Engle and Kroner (1995); BEKK is named after an earlier working paper of Bollerslev, Engle, Kraft and Kroner). Moreover, a VEC or VECH formulation is also readily available.

1987. There is no reason to exclude these outliers since they reflect the nature of the market. The raw data series for individual assets are grouped into portfolios as described in section 2.2. The dataset is therefore composed of event portfolios, non-event portfolios and one market index. The event and non-event portfolios are divided into seller (S), acquirer (A) and both seller and acquirer (B) portfolios. We define three different event period windows; (1) from 10 days before to 1 days after an announcement (PE{-10,+1}); (2) from 20 days before to 5 days after the announcement (PE{-20,+5}); and finally (3) from 40 days before to 40 days after the announcement (PE{-40,+40}). The non-event portfolios are formed by a random selection of event firms consisting of selling (PSNE), acquiring (PANE) and both selling and acquiring firms (PBNE), respectively. All firms in the non-event portfolios exclude event periods of -40 to +40 days relative to announcements. In case of several announcements for an individual firm all periods –40 to +40 days relative to announcements are excluded.

{Insert Table 1 about here}

Therefore, this daily time series database gives us potentially 2611 observations for each portfolio and index. This number of observations provides enough degrees of freedom to permit use of asymptotic tests. However, the event portfolios will most likely consist of a varying number of assets over dates and especially the shortest event period window will consist of a number of missing observations. Hence, all the sample sizes will be reported. The characteristics of the raw data from event and non-event equally weighted asset portfolios and the value weighted market index, are reported in Table 1.

The following immediate observations can be made. The mean returns are highest for the seller firm event portfolios in the two narrowest announcement period windows. The longest time period window for the selling companies show a considerably lower daily mean return. Moreover, compared to all other portfolios, the daily return standard deviations for selling firm portfolios are the highest for all three event period portfolios. For the shortest event period the mean return is 5 times and the standard deviation 3 times as high as the market index values. The same numbers for the acquiring portfolios are considerably smaller. That is, both expected return and standard deviation are highest for the event portfolios formed from selling firms. The non-event portfolios show results close to the market index. Hence, Table 1 suggests event-induced price and return turbulence. Figure 1, panel A, plots the raw value weighted market index. From this time series it seems to exist several periods of high volatility followed by periods of lower volatility. However, any pattern is not readily observable from the plots.

{Insert Figure 1 about here}

Following Gallant, Rossi and Tauchen (1992) many authors have noted systematic calendar effects in both mean and volatility of price movements. Hence, we adjust all portfolio and index time series by regressing the scaled returns on the set of adjustments variables: $\omega = x'\beta + u$ (mean equation). The adjustment variables consist of dummy and time-trend variables. The least square residuals are taken from the mean equation to construct a volatility equation: $ln(u^2) = x'\gamma + \varepsilon$. Finally, a linear transformation is performed to calculate adjusted return series (ω): $\omega_{adj} = a + b*(u/exp(x'\gamma/2))$, where a and b are chosen so that the sample means and volatility of ω and ω_{adj} are identical. This adjustment procedure for all portfolios and the value-weighted index allow us to focus on the day-to-day dynamic structure under an assumption of stationary series. We plot the adjusted value weighted index in Figure 1 Panel B. As for the index, all event and non-event portfolios show an adjusted time series that become more homogenous over time. Further discussion of the effects from the adjustment procedure is found in Gallant et al. (1992). Owing to space requirements we do not report details from the adjustment results[6].

To get an idea of the return distributions of the portfolio and index series, we have also reported the kurtosis and skew in Table 1. The numbers report leptokurtosis in all series. We find too much probability mass around the mean and too low probability mass around 1 and 2 standard deviation from the mean. The numbers for the skew is strongly negative for the market index and strongly positive for the shortest event firm portfolios. Hence, the event portfolios show more positive extreme return values than negatives in contrast to the market index. The kurtosis and skew suggest that the returns are not normally distributed. Hence, to accomplish this deviation from normality we employ a student t-density distribution in the log-likelihood function for the GARCH estimation. For the bivariate GARCH estimation (MGARCH) we assume a multi-normal distribution.

Finally, the portfolios and the index all report significant ARCH test statistics. The test statistic suggest volatility clustering and make the (G)ARCH methodology employable for all our sample series.

4 Empirical Results for Univariate Time Series

4.1 The univariate and asymmetric ARMA-GARCH-in-Mean[7] specification

Maximum likelihood estimates of the parameters in equation (1), (2) are given in Table 2 for a student-t density log-likelihood function. The constant ϕ_0 in our model is expected to be positive showing a positive drift. All the ϕ_0's are insignificant, which suggest that all the series cannot report a non-zero drift.

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[6] The results are readily available from the author upon request.
[7] All series and the market index BIC prefers p=0 and q=m=n=1.

Non-synchronous trading or serial correlation is negative and statistical significant for the market index and all non-event portfolios except selling firms. This result suggests that the selling firms are thinly traded assets. The event series show all negatives or close to zero autocorrelation coefficients. However, for the shortest event period window, the series show insignificant coefficients. Hence, the market is reasonable information efficient in expectation of announcements (immediate adjustment). Our results therefore suggest that non-synchronous trading may be important to control for in classical event studies.

{Insert Table 2 about here}

The parameter for residual risk and contemporaneous conditional volatility (β) is negative but insignificant for all portfolios. The result suggests an insignificant negative relationship between return and volatility, which suggest lower returns in high volatility regimes. The insignificance may also suggest higher relevance for systematic risk (market risk) as suggested by several asset-pricing models. The in-Mean formulation seems therefore to be redundant in these ARMA-GARCH models.

Among the estimated conditional volatility ARCH/GARCH coefficients for the GARCH specification reported in Table 2, which are all strongly significant, we find clear patterns. Firstly, the constant coefficient m_0 in the conditional volatility process in the GARCH model is small but significant for the index, non-event series and the longest event periods. The result suggests a significant coefficient for unexplained conditional volatility. For the two narrowest event windows we find a strong increase in the m_0 coefficient, which suggests a strong increase in unexplained conditional volatility, which most likely is attributable to the events. The increase is especially strong for series consisting of selling firm. Secondly, the past squared errors have more influence over the conditional volatility of the two narrowest event portfolios than they do over the conditional volatility of the non-event portfolios and the index. The result suggests more sensitivity to past shocks for event portfolios relative to non-event portfolios. Thirdly, in contrast to the squared past error, the past conditional volatility exerts a greater influence over the current conditional volatility for non-event portfolios than event portfolios. Hence, the autocorrelation in the conditional volatility process is lower for event portfolios. For especially the event series most centred on the announcement day, we find low coefficients for the past conditional volatility. The parameter for asymmetric volatility is significant and negative for the index and all non-event portfolios. None of the event portfolios report significant asymmetric volatility. Our results therefore suggest that asymmetry may be redundant in event periods but is required in on-event periods.

{Insert Table 3 about here}

Summary values for the conditional volatility process ($h_{i,t}$) are reported in Table 3. Table 3 clearly indicates event-induced volatility. Highest relative conditional volatility increase is found for selling firm series. Our results indicate a 3 to 4 times mean increase in the conditional volatility. Also the acquiring firm series report an increase in the conditional volatility, but clearly smaller than selling firms. Hence, results suggest a need to control for the increased volatility in the event periods, for especially selling firms.

{Insert Table 4 about here}

Finally, as a specification test of our ARMA-GARCH models, we calculate the sixth order Ljung-Box (1978) statistic for the standardised residuals and squared residuals of each of the portfolios and the market index's expected returns in Table 4. In each portfolio there are no significant evidence of serial correlation (1%) in the residuals and squared residuals up to lag 6. The kurtosis is strongly reduced and all portfolios show lower absolute skews for the standardised residuals. In comparison to the adjusted raw returns the K-S Z-test confirms the more normal distributed residuals. The two features, close to normal residuals and the highly significant student-t density parameter υ_t seem to emphasis the importance of thick tails estimations. Our results therefore suggest that student-t densities in the log-likelihood function are preferred in classical event studies. The ARCH tests report no conditional heteroscedasticity in the standardised residuals. Hence, all conditional heteroscedasticity is captured by the GARCH specification of the conditional volatility. The BDS (Brock et al., 1991, 1995) test statistic shows insignificant values at all dimensions (m) and $\varepsilon = 1$ standard deviations. Hence, no data dependence and non-linearity is found in the standardised residuals. However, the joint bias tests (Engle and Ng, 1993) report some significant test statistics. Hence, we will find some bias in the conditional volatility prediction. However, overall our specification test results indicate that the current univariate and asymmetric ARMA-GARCH models are appropriate models for stock returns in event studies. Moreover, analytical, intuitive and linear reasoning may be conducted as we find insignificant test statistics for data dependence in all series.

5 The Bivariate and Asymmetric ARMA (p,q)-GARCH (m,n)-in-Mean[8] specification

Maximum likelihood estimates of the parameters for the bivariate GARCH-in-Mean model are presented in Table 8A and 8B for all portfolios. The bivariate estimation controls for market dynamics by incorporating a value-weighted market index into the estimation. The two intercepts (ϕ_0 and ϕ_M) in the mean equations from our bivariate system in Table 5A are positive indicating a positive drift.

[8] All portfolios and the market index BIC prefer q=m=n=1.

Autocorrelation is present in all bivariate estimations except for selling firms. The market index shows negative and significant autocorrelation coefficients for all estimations. The event series show all significant negative coefficients except for the two selling firm series most centered on the announcement day. Our results therefore suggest that coefficients for non-synchronous trading are needed in almost all the bivariate event estimations. Cross-autocorrelation from index to event series is significant for all series.

The GARCH-in-Mean parameters can be reported for several alternative outlines of the mean equation. However, we estimate and report only the diagonal volatility matrix in the mean equation (only variances). The event series volatility may be interpreted as residual risk and can be considered as a proxy for omitted risk factors (Lehmann, 1990). None of the portfolios and the market index report significant "in-Mean" coefficients. Hence, the "in-Mean" specification seems therefore redundant.

{Insert Table 5A and 5B about here}

From Table 5B the t-statistics indicate that all the conditional volatility parameters are almost all statistical significant. This result cast doubt on the validity of the univariate model specification. The constant coefficients in the conditional volatility equations report the same effects as for univariate estimations. The constant term m_{11} show considerable increases in especially the selling firm event portfolios compared to the non-event firm portfolios. This result implies that there is an increase in conditional volatility that is not possible to explain by the ARCH/GARCH coefficients alone (unexplained increase). The increase is also found for the constant term m_{22}. However, the increase is considerably smaller than for m_{11}. Moreover, the increase is higher the narrower the event period and therefore shows the highest non-explainable conditional volatility. For the past squared errors we find that the event series most centred on the announcement day are considerably more sensitive to past shocks than the non-event portfolios. In contrast the past conditional volatility exerts a greater influence over the current conditional volatility in the case of the non-event series. Moreover, as for the univariate estimations, the past conditional volatility coefficients show a decrease the shorter the event period for selling and acquiring firm series. We report values for the conditional volatility process ($h_{i,t}$) in Table 6. The results for the $h_{i,t}$ processes are very similar to that obtained in the univariate estimations. Moreover, $h_{i,t}$ produces mainly the same time series plots. Table 6, as Table 4 for the univariate case, clearly indicates event-induced volatility. Highest relative conditional volatility is found for the selling firm series. Hence, also our bivariate results indicate a 3 to 4 times mean increase in the conditional volatility for selling firms. Moreover, we find that the acquiring firm portfolios show an increase in the conditional volatility, but clearly smaller than selling firms. Therefore, as for the univariate case, our bivariate results suggest a need to control for volatility clustering in event studies.

{Insert Table 6 about here}

As for univariate models, specification tests of the bivariate model are performed. We find no significant serial correlation in the residuals and squared residuals up to lag 6. Furthermore, the bivariate cross-correlation series for -10 and 10 lags are calculated and checked (not reported). The result suggests very low to no significant cross-correlation in any lag for all bivariate ARMA-GARCH-in-Mean estimations. All portfolios and the market index show excess kurtosis for the standardised residuals. Almost all portfolio residuals show negative skews, except for the narrowest event portfolios. Moreover, the bivariate estimations, report lower kurtosis and skews than the univariate estimations. However, the K-S Z-test still reports non-normal standardised residuals for almost all portfolios and the index. The ARCH test statistic reports no volatility clustering in the standardised residuals. The BDS test statistic for i.i.d. reports that none of the portfolios show significant non-linear dependence at any dimension. Finally, the joint bias test reports no prediction bias for the conditional volatility. Hence, our bivariate model survives the specification tests and is at the same time a parsimonious model, which is able to capture dynamic structure.

{Insert Table 7 about here}

Since the market seems to play an important role, an univariate representation of the conditional volatility of stock returns will be disputed. Moreover, the specification tests unambiguously prefer a bivariate estimation technique.

6 The changes in conditional volatility

To test for the changing volatility hypothesis from non-event to event firm samples, we perform a Likelihood Ratio Test (LRT). This test is a general test for testing the restrictions imposed on a model. The model is first estimated without any restrictions. The model is then re-estimated with the restrictions in place. Under the null hypothesis, LRT is distributed as χ^2 with number of restrictions as degrees of freedom. For our analysis we restrict the event samples GARCH parameters to be within the intervals obtained from non-event samples GARCH parameters. As we employ a GARCH (1,1) lag specification we introduce 6 restrictions on the event sample GARCH estimations. We report the LRT values with corresponding test statistics in Table X.

{Insert Table 8 about here}

Table 1 report a significant change in parameter values for both univariate and bivariate estimations from non-event to event samples. The LRT test statistics rejects unchanged parameter values for all event series. Hence, our results suggest a significant increase in conditional volatility. The increase suggests a need for new event methodologies controlling for this increase as well as the significant non-synchronous trading effects in all our samples.

Therefore in Section 7, we suggest two alternative events study techniques, a univariate and a bivariate specification that models non-synchronous trading and volatility clustering. Note that we in the univariate specification do not control for non-synchronous trading and volatility clustering in the market index.

7 ARMA-GARCH Specifications for event study methodology

Our results suggest that we find different mean and volatility effects during event and non-event periods. Our findings therefore suggest a need for more advanced techniques for calculation of abnormal returns in classical event studies. In this paper we have shown that both univariate and bivariate GARCH-in-Mean models indicate higher conditional volatility for event portfolios relative to non-event portfolios. Hence, our results suggest event study models that put emphasis on non-synchronous trading and volatility clustering. ARMA mean equations emphasis non-synchronous trading and GARCH volatility equations emphasis volatility clustering.

Hence, our results suggest either a univariate or a bivariate ARMA-GARCH specification for estimation of abnormal return during event periods. Below we define these models for use in classical event studies employing the market model.

The first model is the univariate ARMA(p,q)-GARCH(m,n)-in-Mean model for individual assets. Based on our results from Section 4, this model becomes

$$R_{j,t} = \phi_{j,0} + \sum_{i=1}^{p} \phi_i \cdot R_{j,t-i} + \beta_{j,1} \cdot R_{M,t} + \xi_k \cdot D_{j,i,t} + \varepsilon_{j,t} - \sum_{i=1}^{q} \theta_i \cdot \varepsilon_{j,t-i}$$

where $j = 1, ...,N$ event firms, $R_{M,t}$ is the appropriate raw exogenous market index, $D_{j,i,t}$ is a dummy variable with value 0 outside the event period and 1 inside the event period. The definition of $D_{j,i,t}$ decides the length of the event period. $E(\varepsilon_{i,t} \mid \Omega_{t-1}) \sim D(0,h_{i,t},\upsilon_i)$ is the student t-density distribution with υ degrees of freedom. Finally we define the $h_{i,t}$ employing the asymmetric GARCH(m,n) formulation for the conditional volatility process

$$\lambda_{j,i,t} = \gamma_{j,i} \quad \text{if and only if} \quad \varepsilon_{j,t-i} < 0$$

$$E(\varepsilon_{j,t} \mid \Omega_{t-1}) = h_{j,t} = m_{j,0} + \sum_{s=1}^{m} (a_{j,s} + \lambda_{j,s,t}) \cdot \varepsilon_{j,t-s}^2 + \sum_{u=1}^{n} b_{j,u} \cdot h_{j,t-u} + c_{j,t} \cdot D_{j,i,t}$$

where $\varepsilon_{j,t}$ is the return for firm j day t; $\gamma_{j,t}$ is leverage effects (asymmetry), $m_{j,0} > 0$, $a_{j,1}, b_{j,1} \geq 0$, $a_{j,1} + b_{j,1} < 1$, and Ω_{t-1} is the set of all available information at time $t-1$. The model captures non-synchronous trading and volatility clustering for every asset j. However, the $R_{M,t}$ is the adjusted raw market returns.

The second proposed model is the bivariate ARMA(p,q)-GARCH(m,n)-in-Mean model. This model becomes[9]:

$$R_{j,t} = \phi_{j,0} + \sum_{i=1}^{p_j} \phi_i \cdot R_{j,t-i} + \beta_{j,1} \cdot \varepsilon_{M,t} + \delta_{j,k} \cdot D_{j,k,t} + \varepsilon_{j,t} - \sum_{i=1}^{q_j} \theta_i \cdot \varepsilon_{j,t-i}$$

$$R_{M,t} = \phi_{M,0} + \sum_{i=1}^{p_M} \phi_{M,i} \cdot R_{M,t-i} + \varepsilon_{M,t} - \sum_{i=1}^{q_M} \theta_{M,i} \cdot \varepsilon_{M,t-i} \qquad \textit{and}$$

$$H_{s,t} = m_{s,0}' \cdot m_{s,0} + \sum_{u=1}^{m} A'_{s,t-u} \cdot \varepsilon_{s,t-u} \cdot \varepsilon'_{s,t-u} \cdot A_{s,t-u} + \sum_{u=1}^{n} B'_{s,t-u} \cdot H_{s,t-u} \cdot B_{s,t-u} \;\; ; \;\; s=j,M,$$

where $\varepsilon_t \,|\Omega_{t-1} \sim N(0,H_t)$. ϕ_0 is 2 x 1 vector of constants, $m_{s,0}$, A_s, B_s are 2 x 2 parameter matrices, and the elements of $H_{s,t}$ are $h_{j,t} = var_t(r_{j,t})$, $h_{j,M,t} = cov_t(r_{j,t}, r_{M,t})$, and $h_{M,t} = var_t(r_{M,t})$. To allow for the leverage effect and asymmetric volatility we apply the GJR methodology $(\lambda_{j,1}, \lambda_{M,1})$ (Glosten et al., 1993) modeled as for univariate specifications. Note, that only the asset series will employ an event period dummy ($D_{j,k,t}$) for the bivariate estimation.

Among the two model specifications above for the market model in event studies we prefer the bivariate GARCH specification. The main reason for this choice is that we are able to control for non-synchronous trading (autocorrelation and cross-autocorrelation) in the conditional mean and volatility clustering and asymmetric volatility in the conditional volatility for both the asset series and the market index series. As we have shown above and in Solibakke (2000a, 2000b) these effects are important to control in especially thinly traded markets. Moreover, the index and asset series need to be flexibly modelled to allow for market dynamics. The bivariate model controls the co-moments of asset and index series. Hence, unadjusted statistics for the significance of abnormal return may appropriately be applied.

7 Summaries

This paper has estimated an univariate and a bivariate ARMA-GARCH-in-Mean specification for the conditional mean and volatility equations for event and non-event series in the Norwegian thinly traded equity market. The univariate model assumes a student-t density log likelihood function. Both models report strongly higher conditional volatility in event periods. Specification tests suggest that both models capture both non-synchronous trading and volatility clustering in return series. Moreover, specification tests suggest that both univariate and bivariate specifications reject data dependence but some bias in conditional volatility predictions exists. Formally we test for changing volatility in event periods applying a likelihood ratio test statistic for parameter restrictions obtained from non-event periods. All LRT test rejects unchanged parameter estimates.

Finally, the observed coefficient significances of the conditional mean and volatility equations, the strong increase in volatility for observed event series, suggest that event studies should be conducted within bivariate ARMA-GARCH lag specifications. Moreover, owing to removed biases in the moments and co-moments, abnormal returns calculations can apply unadjusted test statistics.

References.

Berndt, E.R., B.H. Hall, R.E. Hall and J.A. Hausman, 1974, Estimation and Inference in Nonlinear Structural Models, Annals of Economic and Social Measurement, 4, 653 - 65.

Boehmer, E. et al., 1991, Event-study methodology and event-induced volatility, Journal of Financial Economics 30, pp. 253-272.

Bollerslev, Tim, 1986, Generalised Autoregressive Conditional Heteroscedasticity, Journal of Econometrics, 31, 307-27.

Bollerslev, Tim, 1987, A Conditionally heteroscedastic Time Series Model for Speculative Prices and Rates of Return, Review of Economics and Statistics, 64, 542-547.

Bollerslev, Tim, Ray Y. Chou og Kenneth F. Kroner, 1992, ARCH modelling in finance. A review of the theory and empirical evidence, Journal of Econometrics, no. 52, 5-59.

Box, G.E.P. and G.M. Jenkins, 1976, Time Series Analysis: Forecasting and Control, Revised Edition, San Francisco, Holden Day.

Brock, W.A. and D.A. Hsieh, B. LeBaron, 1991, Nonlinear dynamics, chaos, and instability. MIT-Press, Cambridge, MA.

Brock, W.A. and P.J.F. de Lima, 1995, Nonlinear time series, complexity theory, and finance. Handbook of Statistics, G.S.Mandala and C.R.Rao (eds.), no. 14, North Holland, Amsterdam.

Brown, K. et al, 1988, Risk aversion, uncertain information, and market inefficiency, Journal of Financial Economics 22, pp. 355-385.

Brown, K. et al, 1989, The effect of unanticipated events on the risk and return of common stock, Working paper (university of Texas, Austin, TX).

Cambell, John Y., Andrew W. Lo and A. Craig MacKinlay, 1997. The Econometrics of Financial markets, Princeton University Press.

Clark, P.K., 1973, “A subordinated Stochastic Process Model with Finite Variance for Speculative Prices.” Econometrica, no. 41, 135-155.

Eckbo, B.E. and P.B.Solibakke, 1992, Bedriftsoppkjøp og Internasjonalisering: Beta, Tidsskrift for Bedriftsøkonomi 2/91, 1-30.

Eckbo, B.E., 1987, Markedet for selskapskontroll: En oversikt over internasjonale empiriske forskningsresultater. Beta, Tidsskrift for Bedriftsøkonomi 1/87, 54-89.

Engle, R.F., 1982, Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation, Econometrica, 50, 987-1008.

Engle, R.F.and Tim Bollerslev, 1986, Modelling the Persistence of Conditional Variances, Econometric Reviews, 5, 1 - 50.

Engle, R.F., D.M. Lillien and R.P. Robbins, 1987, Estimating Time Varying Risk Premia in the term Structure: the ARCH-M model, Econometrica, 55, pp. 391-408.

Engle, R.F., and V.K. Ng, 1993, Measuring and Testing the Impact of News on Volatility, Journal of Finance, 48, pp. 1749-1778.

Epps, T.W. and M.L. Epps, 1976, The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for the Mixture-of-Distribution Hypothesis, Econometrica, 44, 305-21.

Fama, E.F. et al., 1969, The adjustment of stock prices to new information, International Economic Review 10, 1-21.

Gallant, A. Ronald and George Tauchen, 1989, Seminonparametric Estimation of Conditionally Constrained Heterogenous Processes: Asset Pricing Applications, Econometrica 57, pp. 1091-1120.

Gallant, A. Ronald and George Tauchen, 1991, A Nonparametric Approach to Nonlinear

[9] You may incorporate cross-autocorrelation in the bivariate estimation.

Time Series Analysis: Estimation and Simulation, in E.Parzen, D. Billinger, M. Rosenblatt, M.Taqqu, J.Geweke and P. Caines (eds.), New Dimensions in Time Series Analysis, Springer, New York.

Gallant, A. Ronald, Peter E. Rossi and George Tauchen, 1992, Stock Prices and Volume, The Review of Financial Studies 5 (2), pp. 199-242.

Glosten, L.R., R. Jagannathan and D.E. Runkle (1983), “On the Relation between expected Value and Volatility of Nominal Excess Returns on Stocks”, Journal of Finance, Vol 48, pp. 1779-1801.

Lamoureux, Christopher G. and William D. Lastrapes, 1990a, Persistence in variance structural change and the GARCH model, Journal of Business and Economic Statistics, no. 8, 225-234.

Lehmann, B., 1990, Residual Risk Revisited, Journal of Econometrics 45, pp. 71-97.

Nelson, D.B., 1991, Conditional Heteroscedasticity in Asset Returns, Econometrica, 59, pp. 347-370.

Solibakke, P.B.,2000a, Non-synchronous Trading and Volatility Clustering in Thinly Traded Markets. Working Paper, Molde College.

Solibakke, P.B.,2000b, Non-linear Dependence in Thinly Traded Markets. European Journal of Finance, forthcoming.

Tauchen, G.E. and M. Pitts (1983), “The price Variability-Volume Relationship on Speculative Markets.” Econometica, no. 51, 485-505.