Chapter VIII

Abnormal returns in Thinly Traded Markets: Controlling for Non-synchronous Trading and Volatility Clustering

Abstract

This paper employs a new methodology for classical market model event studies to control for non-synchronous trading and volatility clustering. The investigation employs a bivariate ARMA-GARCH market model for abnormal return calculations for a sample of merger and acquisitions in the Norwegian market of corporate control. As shown by Solibakke (2000a, 2000b) non-synchronous trading and volatility clustering biases moments and co-moments in thinly traded markets. Consequently, the autocorrelation average features of the ARMA models and cross-autocorrelation in Vector ARMA models have shown to represent non-synchronous trading effects, and the GARCH family of conditional volatility processes has shown to represent well the changing and asymmetric volatility of stock returns. Applying these two components for model building together with BIC efficient estimation in both mean and volatility, our investigation may cast doubts on the way abnormal returns are calculated and consequently interpreted in classical ordinary least squares (OLS) event studies. Our results suggest three new interesting insights. Firstly, the bivariate ARMA-GARCH specification in contrast to OLS, reports no significant prior announcement effects (no insiders). The result applies to both selling and acquiring firms. Secondly, in contrast to OLS the bivariate ARMA-GARCH specification reports sustained higher post announcement abnormal returns and significances for selling firms. Thirdly, the bivariate ARMA-GARCH specification, in contrast to OLS, reports no overall significant abnormal returns for acquiring firms. Consequently, our results strongly suggest changes in inference from a classical OLS investigation. Moreover, specification tests report significantly lower model misspecification for ARMA-GARCH than for OLS. We suggest a need for a rework of classical event studies applying our new BIC preferred bivariate ARMA-GARCH lag methodology.

Classification:

Keywords: Event-studies, Mergers and Acquisitions, Non-synchronous trading, Volatility Clustering

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1 Introduction and literature review

In economics and finance a frequently asked measure is the effects of an economic event on the value of a firm. Such a measure can be constructed using an event study. Using financial market data, an event study measures the impact of a specific event on the value of the firm. The usefulness of such a study comes from the fact that, given rationality in the marketplace, the effects of an event will be reflected immediately in the security prices. Thus a measure of the event's economic impact can be constructed using security prices over a relatively short time period. In contrast, direct productivity related measures might require many months or even years of observation. The event study has many applications and especially in economics and financial research, event studies have been applied to a variety of firm specific and economic wide events. In this paper we intend to apply the event study methodology for a sample of mergers and acquisitions in the thinly traded Norwegian equity market[1].

Event study methodology has a long history, which perhaps started by James Dolley's (1933) stock split study. The level of sophistication of event studies increased from the early 1930s until the late 1960s. Examples are John H. Myers and Archie Bakay (1948), C. Austin Barker (1956, 1957, 1958), and John Ashley (1962). The improvements included removing general stock market price movements and separating out confounding events. In the late 1960s seminal studies by Ray Ball and Phillip Brown (1968) and Eugene Fama et al. (1969) introduced the methodology that is essential the same as that which is in main use today. Ball and Brown (1968) considered information content in earnings and Fama et al. (1969) studied the effects of stock splits after removing the effects of simultaneous dividend increases. In the years since the pioneering studies, the work by Stephen Brown and Jerold Warner (1980, 1985) summarizes further modifications. Furthermore, the work of R. Thompson in Jarrow et al. (1995) presented the up to date empirical methods in event studies. However, most studies assume ideal experiments. Hence, econometric problems are assumed to cancel out. Moreover, as Thompson (1995) points out on page 979; *"to incorporate increased variance during event periods into the inference problem is an interesting issue that is not completely resolved in the literature".*

This paper will review the event study methodologies under the hypothesis of non-synchronous trading and volatility clustering in individual asset returns. The economic implication is that events may influence the return generating process other than through a shift in the level of security prices. Firstly, event periods may change trading frequency due to a higher information flow to the market and consequently generally higher financial press coverage. The change in trading frequency may change non-synchronous trading and non-trading effects. Non-synchronous trading suggest that individual asset prices are taken to be

[1] We employ a sample of mergers and acquisitions in Norway from April 1st 1983 to April 1st 1994, a total sample of 512 firms.

recorded at time intervals of one length when in fact, they are recorded at time intervals of other, possibly irregular, lengths. Generally, especially in thinly traded markets, reported closing prices for individual assets do not occur at the same time each day because of non-trading. This non-trading effect induces potentially serious biases in the moments and co-moments of asset returns as shown in Campbell et al. (1997) and Solibakke (2000a, 2000b). Secondly, theory might also imply an increase in residual risk during an event period[2]. Homoscedasticity of the residuals, i.e. their distribution show constant variance, may therefore be strongly disputed. Giaccoto and Ali (1982) and Boehmer et al. (1991) have shown that if homoscedasticity is not the case then standard methodology for measuring the effect of a specific event on security prices, have to be adjusted to take into account the presence of heteroscedasticity. More recently, a number of studies, for example Akgiray (1989) and especially Corhay and Tourani Rad (1994), show that the presence of time dependence in stock return series which, if not explicitly treated, will lead to inefficient parameter estimates and inconsistent test statistics. Solibakke (2000a, 2000b) show these effects in thinly traded markets. For especially thinly traded assets the GARCH model may show misspecification. Moreover, Bera, Bubnys and Park (1988) show that market model estimates under ARCH processes are more efficient. Furthermore, Diebold, Im and Lee (1988) observed that residuals obtained using the standard market model exhibit strong ARCH properties. Thirdly, asymmetric volatility controls for the ‘leverage effect’ (Nelson, 1991, Glosten et al., 1993). The asymmetry may change in periods where the information flow is high relative to more normal flow periods. The effect may be more severe in event periods due to higher sensitivity to negative news as for example announcement from the authorities that they will oppose the merger or acquisition.

Consequently, we examine the impact of correcting the market model applying ARMA-GARCH lag specifications for bivariate time series estimation. While Boehmer et al. (1991) employs OLS and adjust test statistic, we enforce synchronous trading, conditional homoscedasticity and symmetric volatility in our model and apply unadjusted test statistics.

We believe this study extends previous works[3] in several ways. Firstly, we employ a simultaneous dummy variable specification. Hence, the estimation and event period is studied simultaneously and the investigation control for non-synchronous trading, volatility clustering and asymmetric volatility over both the estimation and the event period. Secondly, we employ a bivariate model. Hence, cross-correlation effects in conditional mean and volatility can be controlled for in the estimation. The parameters for the conditional means and the conditional variances are estimated simultaneously for firm series and the market index. Consequently, we obtain synchronous trading, homoscedastic and symmetric volatility for both asset and market index series. Moreover, we obtain contemporaneous market dynamics in both

[2] We do not assume a change in systematic risk (beta). The firm specific (unsystematic) risk may change due to higher information flow and higher financial press coverage.

conditional mean and variance equations. Thirdly, using maximum likelihood, the bivariate GARCH model, in contrast to OLS, have shown to strongly reduce leptokurtosis in return distributions, making the residuals more normally distributed. Importantly, close to normal residuals indicate applying unadjusted test statistics. To my knowledge, our event study is so far therefore the most comprehensive study of mergers and acquisitions in thinly traded markets. Moreover, our bivariate ARMA-GARCH lag specification approach applied to classical event studies and the market model is to my knowledge not previously found in the international event literature.

The paper is organized as follows. Section 2 gives the details of the empirical model for classical event studies. Section 3 discusses the market model properties, criticizes the classical assumptions and shows the necessary adjustments to control for non-synchronous trading, asymmetric volatility and conditional heteroscedasticity. Section 4 describes the data and the empirical test statistics. Section 5 presents the empirical results for the samples and model specifications. Section 6 summarizes and concludes our findings. Appendix 1 reports the same study employing a two-step analysis.

2 The empirical model, residual risk and a measure of variability

We focus on common stock returns. We structure the hypothesis in terms of the event's impact on the rate of return process for the corporation's securities. This hypothesis translates into the hypothesis that the rate of return earned on that security over an interval spanning the first public announcement of the event is more positive than normal. The classical event study methodology set out to measure this abnormal return. For each security *i*, let returns follow a stationary stochastic process in the absence of the event of interest. When the event occurs, the market participants revise their value of the security, causing a shift in the return generating process. The conditional return generating process then becomes

$$R_t = x_t \cdot B + \varepsilon_t \tag{1}$$

for non-event periods and

$$R_t = x_t \cdot B + F \cdot G + \varepsilon_t \tag{2}$$

in an event period, where r_t is the return to a security in period t; x_t is a vector of independent variables not related to the event of interest; B is a vector of parameters; F is a row vector of asset characteristics or market conditions hypothesized to influence the impact of the event on the return; G is a vector of parameters measuring the influence of F on the impact of the event; and finally ε_t is a mean zero disturbance. Hypothesis usually centers on G (Thompson, 1995).

[3] See for example the mergers and acquisition study in Eckbo and Solibakke, 1992.

Most event studies use a non-event period to estimate a forecast model and estimate the event's impact from forecast errors in the event period. An alternative characterization of the conditional return generating process under the same assumptions combines the event and non-event periods into a single model for security *i*. The model becomes

$$R_t = x_t \cdot B + D_j \otimes F \cdot G + \varepsilon_t \tag{3}$$

where now the vectors *R*, ε and *x* contain both event and non-event data while *D* is a column of indicators having zeros for non-event periods and ones in the event periods. This characterization of an event study is in a convenient econometric format. Moreover, the characterization makes it possible to perform event studies for simultaneous event and non-event periods. Note that hypnotized event induced variance obstruct conditional homoscedasticity in classical OLS studies. Hence, applying ARMA-GARCH specifications make changing conditional volatility a part of the model specification, while we still obtains constant unconditional volatility.

Thompson (1995) points out on page 979; *"In an ideal experiment, created in the laboratory, it would be natural for firms to have constant residual variance across event and non-event periods."* Most researchers seem to accept this ideal experiment approach. However, showed by Solibakke (2000c) and noted by Christie (1993), forecast errors seem to have higher variance in event periods than in non-event periods. Solibakke (2000c) show that changing residual risk, measured by volatility, is especially strong for selling firm portfolios around the announcement date. Moreover, Beaver (1968) shows that a change in variance between event and non-event periods is a test whether or not an event report new information to the market. Hence, variance estimation procedures may affect inferences. Hence, our paper proposes a market model event study applying a bilateral ARMA-GARCH methodology controlling for non-synchronous trading, changing and asymmetric volatility for assets and market. Hence, we obtain constant unconditional variance and changing conditional variance across event and non-event periods. Finally, following Thompson (1995) page 980*; "if we assume that omitted variables are drawn independently across the sample from a common population, then the increased variance in the event periods captures the noise added by the sampling variability of the omitted variables."*

The same story can be obtained from time series analysis. These analyses hypnotize that the increased variance in event periods can be caused by an increase in the information flow. Hence, the volatility process distribution has a change from non-event to event period. From economic intuition the increased information flow makes sense. Market microstructure phenomena as rumors, insiders and coincident observers may find information that makes information asymmetric in the market. Trading on for example asymmetric information makes price changes and will possibly increase the volatility of the asset. Therefore, Collins & Dent (1984) suggest scaling the covariance matrix estimated in non-event periods by a factor strongly influenced by the estimated residuals from the event period.

Employing ARMA-GARCH methodology we are able to study the change in mean parameter estimates from classical market model OLS estimates, by modeling the latent volatility process. Hence, we model a changing conditional volatility, but assume a constant unconditional volatility. Any change in inferences and different interpretation of the economic significance of events together with changes in mean parameter distributions will therefore be thoroughly specified and reported.

3 The Market model

3.1 The OLS market model specification with assumptions

Empirical researchers in financial economics widely use the market model for measuring the impact of an event on the shareholders wealth or testing market efficiency. This model relates the returns of an asset, $R_{i,t}$, to the returns of a market portfolio, $R_{M,t}$, through a slope coefficient, β_i, which is the asset's market and relevant risk

$$R_{it} = \alpha_i + \beta_i \cdot R_{Mt} + \varepsilon_i \qquad \text{for } i = 1, 2, \ldots, T \qquad (4)$$

where α_i is the intercept and *T* is the number of periods in the estimation period. Hence, event studies include the contemporaneous rate of return on the market index as *x* in (1). In the ordinary least square (OLS) model, returns on a given asset *i*, are regressed against concurrent returns of the market. The announcement effect, *F˙G*, is estimated by the market model forecast error cumulated over the event period(s). Fama, Fisher, Jensen, and Roll (1969) suggested this OLS returns model in their study of stock splits. However, *x* may include the return on similar firm or portfolio of similar firms that do not have the event of interest[4].

Certain assumptions have, however, to be satisfied to have efficient parameter estimates and consistent test statistics based on them. The first assumption is constant coefficients for the market model over time. Iqbal and Dheeriya (1991) resist this assumption and employ a random coefficient regression model allowing betas (β) to vary over time. They argued that the differences in abnormal returns obtained using the market model and their model can be attributed to the randomness in the beta coefficients. Secondly, Scholes and Williams, 1977, have recognized the potential for bias in the OLS β_i estimates due to non-synchronous trading. For securities traded with trading delays different than those of the market, OLS β_i estimate are biased. Likewise, for assets with trading frequencies different than those of the market index, OLS β_i estimate are biased. For actively traded stocks, the adjustments are generally small and unimportant. However, for thinly traded assets, trading frequency in isolation and in contrast to the market index is a real threat to the abnormal return results. Thirdly, classical studies assume homoscedasticity of the OLS residuals (constant variance). Giaccoto and Ali

[4] See Solibakke, 1999c for portfolios in event and non-event periods.

(1982) and Boehmer et al. (1991) have shown that if this is not the case, the standard tests to measure the effect of a specific event on security prices have to be adjusted to take into account the presence of heteroscedasticity.

All three cases suggest a rejection of the simple OLS market model. Below we propose an alternative model specification adjusting for non-synchronous trading and changing and asymmetric volatility (heteroscedasticity).

3.2 The Bivariate ARMA-ARCH/GARCH specification[5] of the market model

Time-varying parameters, non-synchronous trading and temporal time dependence in stock return series can all be handled by an ARMA -ARCH/GARCH methodology employing market model event study. ARMA is applied for the conditional mean (Mills, 1990) and GARCH is applied for the conditional volatility (Bollerslev, 1986). ARCH/GARCH methodology was first introduced by Engle in 1982 and refined and extended by Bollerslev in 1986 and 1987. Engle and Kroner extended the models to the multivariate case in 1995[6].

The diagonal bivariate ARMA (0,q)–GARCH (m,n) market model, adjusting for non-synchronous trading *(θ_i, θ_M)*, asymmetric volatility *(γ_i, γ_M)* and conditional heteroscedasticity (Solibakke, 2000c), is defined as

$$R_{i,t} = \alpha_i + \sum_{j=1}^{p_i} R_{i,t-j} + \beta_{i,1} \cdot \varepsilon_{M,t} + \gamma_{i,j}^{e} \cdot \mathrm{D}_{\mathrm{i,j,t}}^{\mathrm{e}} + \varepsilon_{\mathrm{i,t}} - \sum_{j=1}^{q_i} \theta_{\mathrm{i,j}} \cdot \varepsilon_{i,t-j} \tag{5}$$

$$E(\varepsilon_{i,t}^2 \mid \Phi_{i,t-1}) = h_{i,t} = m_i + \sum_{j=1}^{m} a_{i,t-j} \cdot \varepsilon_{i,t-j}^2 + \sum_{j=1}^{n} b_{i,t-j} \cdot h_{i,t-j} + \gamma_{i,1}^{v} \cdot D_{i,t}^{v} \cdot \varepsilon_{i,t-1}^2 \tag{6}$$

$$R_{M,t} = \alpha_M + \sum_{j=1}^{p_M} R_{M,t-j} + \varepsilon_{M,t} - \sum_{j=1}^{q_M} \theta_{M,j} \cdot \varepsilon_{M,t-j} \tag{7}$$

$$E(\varepsilon_{M,t}^2 \mid \Phi_{M,t-1}) = h_{M,t} = m_M + \sum_{j=1}^{m_M} a_{M,t-j} \cdot \varepsilon_{M,t-j}^2 + \sum_{j=1}^{n_M} b_{M,t-j} \cdot h_{M,t-j} + \gamma_{M,1}^{v} \cdot D_{M,t}^{v} \cdot \varepsilon_{M,t-1}^2 \tag{8}$$

where $R_{i,t}$ is the asset and $R_{M,t}$ the index return in period t; $\varepsilon_{i,t}$ and $\varepsilon_{M,t}$ are the error terms for the two mean equations (5) and (7) in period t, $\theta_{i,j}$ and $\theta_{M,j}$ are the non-synchronous trading parameters at lag j and $\gamma_{i,j}^{e}$ is the event window *j's* abnormal return for firm i. m_i and m_M are the constant terms in the conditional volatility equations; $a_{i,j}$ and $a_{M,j}$ are the parameters for the

[5] For application see Bollerslev et al. 1992.
[6] Two formulations are available: BEKK formulation (Bollerlev, Engle, Kraft and Kroner) and VEC(H) formulation. VEC(H) formulation allows non-positive conditional variance (H_t).

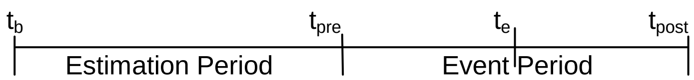
lagged squared error at lag *j*; $b_{i,j}$ and $b_{M,j}$ are the parameters for the lagged conditional variance at lag *j*; $\gamma_{i,1}$ and $\gamma_{M,1}$ are the parameters for asymmetric volatility where $D^{v}_{i,t}$ ($D^{v}_{M,t}$) is a dummy variable taking the value one when $\varepsilon_{i,t-1}$ ($\varepsilon_{M,t-1}$) is less or equal to zero. The ARMA (p,q) specification in (5) and (7) for the bivariate conditional mean is a autocorrelation specification that is able to model non-synchronous trading. The GARCH (m,n) specification in (6) and (8) for the bivariate conditional volatility specify time-varying and symmetric conditional volatility (h_t). Note, as shown in Solibakke (2000c) the in-Mean specification is redundant for bivariate specifications. The bivariate ARMA-GARCH model allow for non-linear intertemporal dependence in the residual series (Solibakke, 2000b). Bera, Bubnys and Park (1988) showed market model estimates under ARCH processes are more efficient. Moreover, Diebold, Im and Lee (1988) observed that residuals obtained using the standard market model exhibit strong ARCH properties. Solibakke (2000a and 2000c) shows that employing ARCH (5) or GARCH (1,1) specification removes all ARCH-effects in residuals applying Norwegian individual asset, portfolio and index series.

Many authors before us have identified the hazards ignoring non-synchronous trading and event-induced variance in event studies[7]. As we already noted in Section 2, non-synchronous trading and changing and asymmetric volatility may lead to inefficient parameter estimates and inconsistent test statistics. As we here employ ARMA-GARCH methodology we may obtain synchronous trading, conditional homoscedasticity and symmetric volatility. Hence, as our specification removes several OLS assumption, we may obtain a sounder basis for event-studies.

4 Event Study Methodology

4.1 Event and Non-Event periods; issues in methodology

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 it is related to the release of information to market participants through the financial press (e.g., Børskurslisten, Aftenposten, Dagens Næringsliv). Normal or predicted returns for an asset are those returns expected if no event occurs. For merger and acquisitions most event studies measure normal returns by estimating normal market model parameters over a time period prior to the period immediately surrounding the event date. The time line for a typical event study for merger and acquisitions may therefore be represented as follows



[7] See Boehmer et al, 1991, Brown, 1988, 1989.

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. Post event-period data will not be employed of obvious reasons.

In the literature we usually find a selection of t_{pre} equal to -40 days to t_e and t_{post} equal to + 40 days of t_e. The length of the estimation period is a weigh of benefits of a longer period and the cost of a longer period. Usually, we find a choice from 12 to 14 months prior to the event announcement (t_e). Hence, from 230 to 270 daily return observations. This event study like most events studies, use the non-event period to estimate a forecast model and estimate the event's impact from forecast errors in the event period. In addition, we employ the alternative characterization of the conditional return generating process under the same assumptions. Hence, we combine the event and non-event periods into a single model for security *i*. The two models are referenced as (2) and (3), respectively, in section 2 above. This approach maintains an algebraic equality between forecast errors from a two-step approach and the individual event period multiple regression event parameters. Finally, if an asset is involved in merger and acquisitions in the estimation period, we exclude a 10-day price period for this asset around the earlier event day.

4.2 Abnormal returns and statistical significance

4.2.1 Estimation in an Estimation Period and Forecasting Abnormal Returns

The abnormal returns (also referred to as the excess stock return or the prediction error) for an individual security for a given period is the difference between the observed return for that period and the expected or predicted return for that period: $AR_{i,t} = R_{i,t} - R^*_{i,t}$, where $AR_{i,t}$ is the abnormal security return for security *i* in period *t*; $r_{i,t}$ is the return on security *i* in period *t*; and $r^*_{i,t}$ is the expected return on security *i* in period *t*. The market model suggested by Fama, Fisher, Jensen, and Roll (1969) is employed for R^*_{it}. Aggregation of the individual security abnormal returns requires examining the cross section of abnormal returns for each period, where each period is relative to t_e, and t_e may be a different calendar time period for each security; thus, abnormal returns are aligned in event time. The mean abnormal return on a given day *t* for a portfolio of securities, $AR_{N,t}$, is the arithmetic mean of $AR_{i,t}$ for the particular day *t*: $AR_{N,t} = \frac{1}{N} \cdot \sum_{i=1}^{N} AR_{i,t}$. Now to calculate the cumulative effect, the individual $AR_{N,t}$ are accumulated over a number of periods to produce a cumulative abnormal return (*CAR*): $CAR_{N,t} = \sum_{t=T_1}^{T_2} AR_{N,t}$, where $CAR_{N,t}$ is the cumulative abnormal return for *N* securities for a period of length n; T_1 and T_2 is the first and last period in which the $AR_{N,t}$ are accumulated. The statistical tests related to abnormal stock returns require the use of the standard error of the forecast. For the market model, the standard error of the forecast for period t is:

$$s_{i,f,t} = s_{i,e} \cdot \left\{ 1 + \frac{1}{T} + \left[\frac{(R_{Mt} - R_M)^2}{\sum_{j=1}^{T} (R_{Mj} - R_M)^2} \right] \right\}^{\frac{1}{2}}$$

, where $s_{i,f,t}$ is the standard error of the forecast for security i in period t in the event period; T is the number of periods employed in the regression equation for parameter estimation; $R_{M,j}$ is the market return for period j within the estimation period; $R_{M,t}$ is the market return for period t within the estimation period; R_M is the mean return on the market over the estimation period; and $s_{i,e}$ is the standard error of the estimate for security i over T periods in the estimation period. Dividing the abnormal return by its estimated standard error yields a standardized abnormal return for a particular security on a given day: $SAR_{i,t} = \dfrac{AR_{i,t}}{s_{i,f,t}}$, where $SAR_{i,t}$ is the standardized abnormal return for security i in period t. The portfolio or sample standardized abnormal returns for a given day t are summed and divided by the square root of the number of securities in the portfolio:

$$SAR_{N,t} = \frac{1}{\sqrt{N}} \cdot \sum_{i=1}^{N} SAR_{i,t}$$

, where $SAR_{N,t}$ is the standardized abnormal return for a group of N securities on day t. If $SAR_{i,t}$ are independent and identically distributed with a finite variance, $SAR_{N,t}$ is distributed unit normal for large N. Finally the standardized cumulative abnormal return for a group of N securities, $SCAR_{N,n}$, can be calculated as:

$$SCAR_{N,n} = \frac{1}{\sqrt{N}} \cdot \sum_{t=1}^{n} SAR_{N,t}$$

, where $SCAR_{N,n}$ is the standardized cumulative abnormal return for a group of N securities over n periods. $SCAR_{N,n}$ is assumed to be distributed unit normal in the absence of abnormal security performance.

However, this specification of the abnormal return is a two-step analysis where the event induced variance is measured through the $s_{i,f,t}$ term. As shown by Solibakke (2000c) the $s_{i,e}$ term is significantly lower during non-event periods than in event periods. Adjusting by employing the $s_{i,f,t}$ term will only measure volatility changes on the total market level. This seems not to be an adequate adjustment. Appendix 1 confirms this assertion. Relative to the simultaneous analysis described in the next section, the two-step ARMA-GARCH specification seems not to be worth the effort.

4.2.2 Simultaneous Estimation and Abnormal Return Calculation

As shown in Section 2, a convenient alternative characterization of the conditional return generating process under the same assumptions, we combine the event and non-event periods into a single model for security *i* applying the form

$$R_i = \hat{\alpha} + \hat{\beta}_i \cdot R_M + \gamma_i \cdot D_i + \varepsilon_i \tag{9}$$

where now the vectors R_i, ε_i, R_M and ε_M contain both the event and non-event data while D_i can be viewed as a matrix of zero-one variables, letting each column indicate a single event period. γ_i can be interpreted as the sum of the individual event period effects. Time series estimates of variability can be combined with estimates of individual asset effects in a number of ways. However, as we wish an unbiased estimate of the mean effect and a test of significance, this study test the significance of the average event effect by using the time series estimates of variability to construct an estimate of variability for the arithmetic mean. To test for significance of the mean event effect, we compute the statistic $\dfrac{\sum_{i=1}^{I}\gamma_i}{\left(\sum_{i=1}^{I}\sigma_i^2\right)^{\frac{1}{2}}}$, where γ_i is the event effect for asset *i* and σ_i is the estimate of the standard error of γ_i around the true event effect for asset *i*. This statistic is equivalent to an OLS regression of forecast errors on a column of ones. Note, however, that standard errors from OLS cross-sectional regressions are often ignored because they fail to account for neither non-synchronous trading nor conditional heteroscedasticity.

5 Data

The study uses daily continuously compounded returns of individual Norwegian stocks spanning the period from April 1st 1983 to April 1st 1994. These daily returns are scaled to avoid possible scaling problems in estimation. Data are obtained from Oslo Stock Exchange Information A/S. To proxy for the market we employ the value weighted market index from Oslo Stock Exchange (Totx).

The sample period includes the crash of October 19, 1987. There is no reason to exclude these outliers since they reflect the nature of the market. This high frequency time-series database gives us potentially 2725 observations for each firm and index. The merger and acquisition selling firm sample consists of 126 Norwegian and Foreign (listed on Oslo Stock Exchange) firms. The acquiring firm sample consists of 282 Norwegian and Foreign (listed on Oslo Stock Exchange) firms. For the selling firms the sample is approximately 50% of the population in the period. For the acquiring firms the sample is approximately 65% of the population. The information is retrieved manually from the "Børskurslisten"[8] published by the Oslo Stock Exchange. All forms of mergers and acquisitions are included in the sample[9]. Finally, to secure ergodic and stationary time series we adjust all time series for systematic location and scale effects (Gallant, Rossi and Tauchen, 1992).

Moreover, we apply the BIC (Schwarz, 1978) for p_i, q_i, m_i and n_i and $i = i,M$, lag sizes in ARMA (p,q)-GARCH(m,n) specification. For the value weighted Norwegian market index, the ARMA (0,1) model is preferred (Solibakke, 2000a). Moreover, using the BIC criterion (Schwarz, 1978) on the squared residuals, produce an ARMA (1,1) specification for the index. The result implies a GARCH (1,1) specification for the conditional variance process. Individual assets prefers almost exclusively an ARMA (0,1)–GARCH (1,1) specification. However, some assets prefer p > 0 and q = 0, p=0 and q > 1. None of the assets prefer higher $p=q=n>2$. All assets prefer $m=1$. Hence, the most elaborate specification for individual assets are ARMA (2,2)-GARCH (1,2)[10].

6 Empirical Results from a bivariate ARMA-GARCH specification

The OLS market model is denoted LS_{OLS} and the multivariate GARCH model, is denoted ML_{MGRCH}. In the LS_{OLS} market model the residuals are assumed to have a mean of zero and a constant variance (homoscedastic residuals), while in the alternative ML_{MGRCH} model, residuals can be controlled for non-synchronous trading and conditionally heteroscedasticity. Asymmetric volatility is adjusted for through the terms γ_i and γ_M for asset i and the market index (M), respectively, in the conditional volatility equation. We therefore apply the simultaneous estimation methodology from Section 4.2.2, to fully exploit all the advantages of the ARMA-GARCH lag specifications and to be able to apply unadjusted test statistics.

The average mean event effects for several event periods are reported in line 1 of Table 1 for the OLS regressions and in Table 2 for the bivariate GARCH regressions. Percent negative observations are reported in line 2 and statistical significant average event effects using the defined test statistic in section 4.2.2 are reported in line 3. Standard t-tests are employed using classical significance levels. A Z-statistic is reported in line 4 and is defined as $\frac{G - M \cdot p}{\sqrt{M \cdot p \cdot (1-p)}}$, where G is the number of negative parameter estimates, M is the total number of parameter estimates, and p is the probability of a negative parameter estimate. A null hypothesis of zero event effects set the probability p equal to 0.5. We report our main results below.

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[8] Also "Dagens Næringsliv" and "Aftenposten" are used for collection of information.
[9] The whole list of acquiring and selling firms in the two samples are available from the author upon request.
[10] The BIC preferred lag structure for individual asset must be considered in each estimation while the marked index always prefer the same specification, defined above.

{Insert Table 1 and 2 about here}

We approach the selling firm's sample in Panel A of Table 1 and 2. Firstly, we find no significant prior anticipation in ML_{MGRCH} in contrast to LS_{OLS}. For the event period –10 days to +1 day (*E-10+1*) relative to announcement day (t_e) shows a t-value of 2.00 for the OLS estimation and 1.02 for the bivariate ARMA-GARCH estimation. Even though the average parameter effect has increased in the ML_{MGRCH} specification relative to LS_{OLS}, the standard error of the parameter has increased relatively higher so that the t-ratio becomes insignificant for the MGARCH specification. Our results suggest no abnormal return for selling firms prior to announcement in MGARCH in contrast to OLS. Secondly, the MGARCH model suggests higher significance of abnormal returns in the post announcement day (t_e) period. For post period –1 to +20 relative to announcement day (E–1+20) and –1 to +40 relative to announcement day (E-1+40), the results suggest that the abnormal returns accrue to the shareholders of selling firms the first 20 days of the post event period. The significance of the {E-1+20} calculations is 4.36 in contrast to 4.30, even though the coefficient is lower in the MGARCH estimation; that is 0.3 to 0.26. However, both techniques suggest a substantial abnormal return to shareholders of selling firms. Moreover, we find no reversal effect from day +20 to +40 relative to announcement day in ML_{MGRCH} in contrast to LS_{OLS}.

For the acquiring firm's sample in Panel B of Table 1 and 2, our main finding is that we find no significant abnormal return for any of our pre-defined event periods in ML_{MGRCH}. In the LS_{OLS} specification our results suggests significant abnormal return close to announcement day (E-1+2). Hence, for the ML_{MLGRCH} estimation we find an overall insignificant event effect for acquiring firms. The ML_{MGRCH} results seem to suggest higher information flow and consequently higher volatility (higher standard errors) and hence, insignificant abnormal returns. The observation is interesting and is probably a result of an increase in volatility as documented in Solibakke (2000c) for event periods.

Specification tests are summarized in Table 3. The null hypothesis (H_0), the proportion of OLS misspecifications is the same or less than the proportion of ARMA-GARCH misspecifications are strongly rejected. Hence, overall the ARMA-GARCH model specifies lower degree of misspecifications than the OLS model, which suggests a higher confidence to parameter values. Our results therefore seem to emphasize the finding that our ARMA-GARCH specification results may calculate abnormal return more adequately than OLS.

{Insert Table 3 about here}

The differences observed between these two models are due to the magnitude and dispersion of the α and β estimates over the samples. The properties of α, β and γ[11] from our specifications are reported in Figure 5, 6, and 7, respectively. The distributions of coefficients for LS_{OLS} and ML_{MGARCH} are slightly different over the samples for the three coefficients. The intercept coefficient, α, has a higher positive mean for the LS_{OLS} than the ML_{MGARCH} market model and the standard error is lower for both selling and acquiring firms. The slope coefficient, β, has a slightly lower mean and a slightly higher standard error for the LS_{OLS} than the ML_{MGARCH} specification for acquiring firms. For selling firms the LS_{OLS} mean and standard error for beta (β) are strongly higher than for ML_{MGARCH}. Hence, we find that the sellers are more responsive to market movements, due to non-synchronous trading and conditional heteroscedasticity. The event coefficient, γ, is reported for {E-1+20} for selling firms and {E-1+2} for acquiring firms. For the selling firms we find lower coefficient (0.04) and higher standard deviation (0.09) for ML_{MGRCH} than for LS_{OLS}. Hence, the growth in standard deviation out weights the reduction in the coefficient. For the acquiring firms and event period minus one day to plus two days relative to announcement, we find both a higher coefficient and higher standard deviation. Also here we find a stronger increase in the standard deviation relative to the increase in the coefficient. Hence, for acquirers event coefficients show lower significance in ML_{MGRCH} relative to LS_{OLS}. In contrast sellers show lower significance in ML_{MGRCH} for pre-announcement periods and close to higher significance in post-announcement event periods.

{Insert Figure 1, 2 and 3 about here}

Our results suggest that the ML_{MGRCH} approach for event period estimation seems to be worth the extra effort for the calculation of abnormal returns. The relative large change in variance relative to mean seems indeed to change inferences in event studies. Finally, the results from appendix 1 suggest that the above performed simultaneous event study is the only valid methodology controlling for changing trading frequency and volatility in event periods.

7 Summaries and Conclusions

The main purpose for this paper is to estimate market model parameters in classical market model event studies adjusted for non-synchronous trading and changing and asymmetric volatility. Even though there is no intrinsic interest in estimating the conditional variance, the market model should be estimated by maximum likelihood in order to obtain more efficient estimators of the regression parameters. The lack of efficiency of the least square estimator may result in such a poor estimate that the wrong conclusion may be drawn. Applying ARMA-GARCH methodology and a simultaneous estimation and event period specification, incorporates synchronous trading, constant and symmetric volatility in event studies. The

[11] Minus 1 day to plus 20 days relative to announcement day for selling firms and minus 1 day to plus 2 days relative to announcement days for acquiring firms.

results suggest that the effects may lead to different interpretation of economic significance. The presence of GARCH does not violate the assumptions of the second order properties of the least square estimator. However, the differences in abnormal returns obtained in our study are due to the fact that the coefficient estimates of α and β using the OLS market model are inefficient since they are not adjusted for GARCH (conditional heteroscedasticity). When the OLS market model residuals are tested for the presence of GARCH using the Lagrange Multiplier approach of Engle (1982), a strong evidence of ARCH properties is revealed. The GARCH models resolve this problem, and the estimators are more efficient.

The main results from the multivariate ARMA-GARCH specification suggest that there is no prior anticipation in ML_{MGRCH} for either selling or acquiring firm samples. The around announcement effect for the acquiring firm's sample in OLS estimation, is rejected in the ML_{MGRCH} specification. In fact, for acquiring firms we find no significant event effects at all in the ML_{MGRCH} specification. For selling firms the abnormal return in the post announcement period show increase in both level and significance relative to LS_{OLS}. We find no reversal to zero of abnormal return from day +20 to +40 in ML_{MGRCH} relative to LS_{OLS}. We find no prior anticipation for selling firms in ML_{MGRCH} in contrast to LS_{OLS}. Moreover, specification tests report significantly lower model misspecifications for the ARMA-GARCH than for the OLS specification.

Hence, our findings suggest that ML_{MGRCH} estimation for event studies do indeed change inferences applying a simultaneous estimation and event period investigation. Therefore, applying the simultaneous ML_{MGRCH} methodology, our results suggest that classical studies should be replicated to control for non-synchronous trading and changing and asymmetric volatility often found in classical LS_{OLS} studies. In fact, our results suggest higher market efficiency (no anticipation and reversal) applying the new methodology.

Appendix 1

Empirical Results applying a separate estimation period and forecasting abnormal returns into the event period.

The CAR_t are reported in Table 4 for both selling and acquiring firms. Statistical significant CAR_t*'s* using standard t-tests are marked by * for 10% significance, ** for 5% significance and *** for 1% significance. Figure 4 plot the *CARs* for two different event windows for selling and acquiring firms. Figure 5 reports the OLS-MGARCH differences for selling and acquiring firms, respectively. My first observation is that the differences between *ARs* of the LS_{OLS} and the ML_{MGARCH} specifications in Figure 5 are almost all negative. The average difference is -0.084 (-0.061) for selling (acquiring) firms and associated standard deviation is 0.0722 (0.0265). Hence, for both samples the average differences are negative within one standard deviation. The result suggests that the bivariate ML_{MGRCH} model reports higher abnormal returns in the event periods than the OLS model for both selling and acquiring firms.

The S*CAR* results in Table 5 show for both model specifications that statistical significant *AR* accrues to the acquiring firm shareholders around the announcement days (t_e). I find no significant abnormal returns to the selling firm shareholders around the same announcement date. Prior announcement effects are reported in both LS_{OLS} and ML_{MGRCH} for the period –10 to –1 day relative to announcement day for the sample of selling firms. For the post-event periods in Table 5, we find a significant positive abnormal return for day –1 to +20 days relative to announcement day in both specifications for selling firms. However, the magnitude of AR is strongly higher in the ML_{MGRCH} specification. Moreover, both models suggest a considerable delayed response relative to the event and both the LS_{OLS} and ML_{MGRCH} specifications suggest reversal in period +20 to +40. For the acquiring firms the significance levels are considerably lower. Both OLS and MGARCH report no prior announcement effects. Both models report positive effects around the event date. The ML_{MGRCH} and not LS_{OLS} suggest post announcement effects up to day +40.

{Insert Table 4 about here}

In Figure 4, we observe that the *CARS's* for both model specifications show more or less the same pattern. However, the ML_{MGRCH} model, since almost all *ARs* from the OLS market model are smaller than the ML_{MGRCH} model, the *CARs*-path lie constantly above the OLS path. For the sample of selling firms, the maximum likelihood estimate of the ML_{MGRCH} specification shows significant *CARs* after day +2 in the post event period. In contrast, the LS_{OLS} model only shows significant *CARS* from day 13 to 28. Hence, the LS_{OLS} model seems to under-report abnormal returns for selling firms. The same story repeats for the sample of acquiring firms. The ML_{MGRCH} specification shows significant *CARs* after day +0 in the post event period. In contrast, the LS_{OLS} model shows no significant *CARS* in the same period.

{Insert Figure 4 and 5 about here}

The *CARS* and their respective t-statistics reveals that the ML_{MGRCH} specification produces results that led to a change in inferences from LS_{OLS}. Firstly, for the whole post event period (-1, + 40) and both selling and acquiring firms, the *CARs* from the maximum likelihood model show strong statistical significance in contrast to the LS_{OLS} model. Secondly, for selling (acquiring) firms significant abnormal returns start at day 3 (0) for the ML_{MGRCH} model in contrast to the LS_{OLS} model at day 13 (no significant observations). Thirdly, for selling firms, the LS_{OLS} model reports a significant negative cumulative abnormal return for 20 to 40 days relative to announcement. That is, the selling firm sample shows only a temporal increase in asset value in LS_{OLS}. This effect is considerably lower in both value and significance for the

ML_{MGRCH} model. That is, the maximum likelihood model reports a permanent change in asset value in contrast to ordinary least square. However, the magnitude of the differences in cumulative abnormal returns is surprisingly low after adjusting for non-synchronous trading and conditional heteroscedasticity in the estimation period.

{Insert Table 5 about here}

The differences observed in the CARs of these two models are due to the magnitude and dispersion of the α and β estimates over the samples. The properties of α and β for our two models are reported in Figure 6 and 7, respectively. From these plots we find that the distributions of coefficients for LS_{OLS} and ML_{MGRCH} are slightly different. That is, (1) the intercept coefficient, α, has a higher mean for the LS_{OLS} than the ML_{MGRCH} market model. The standard deviation seems to depend on the absolute value of the mean. The slope coefficient, β, has a lower mean and standard deviation for the LS_{OLS} than the ML_{MGRCH} market model. These two results suggest that the ML_{MGRCH} model produce a lower α and a higher β. That is, a more market sensitive sample for ML_{MGRCH} specifications, which turns out to report a clearly higher positive abnormal return. α and β therefore seem to show differences in distribution characteristics between specifications. However, the significance levels and event patterns are almost identical. The main conclusion is therefore that using LS_{OLS} or ML_{MGRCH} models in the estimation period and then forecast the *AR's* applying standard event methodology in section 4.2.1, show almost identical results and inferences. Hence, we may conclude that the extra effort applying ML_{MGRCH} methodology in a separate estimation period does not pay the effort.

{Insert Figure 6 and 7 about here}

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