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Modeling the Intraday Return Volatility Process in the Australian Equity Market: An Examination of the Role of Information Arrival in S&P/ASX 50 Stocks

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Abstract

This paper examines the intraday return volatility process in Australian company stocks. The data set employed consists of five-minute returns, trading volumes and bid-ask spreads over the period 31 December 2002 to 4 March 2003 for the fifty national and multinational stocks comprising the S&P/ASX 50 index. The GARCH and asymmetric GARCH namely Threshold ARCH (TARCH) processes are used to model the time-varying variance in the intraday return series and the inclusion of news arrival as proxied by the contemporaneous and lagged volume of trade and bid-ask spread together with day-of-week effects are used as exogenous explanatory variables. The results indicate strong persistence in volatility for the fifty stocks even with the day-of-week effects and contemporaneous and lagged volume of trade and bid-ask spread included as explanatory variables in the models. Overall, while there is much variation among the stocks included in terms of the role of the irregular arrival of new information in generating GARCH effects and the degree of persistence, all of the volatility processes are mean reverting.

Keywords: Intraday return volatility, Volume of trade, Bid-ask spreads

1. Introduction

It goes without saying that knowledge of stock return volatility is important. In any number of asset pricing and portfolio management problems this knowledge, as encapsulated in volatility models, is used to make predictions that help market actors make better financial decisions. And already a number of stylized facts are known about stock return volatility and the best models to capture and reflect these stylized facts. In the first instance, these include volatility clustering, persistence and mean reversion whereby volatility shocks today will influence the expectation of volatility in the future, though with some more normal level to where it will eventually return. In the second instance, the autoregressive conditional heteroskedasticity (ARCH) model and its various extensions has been shown to provide a good fit for many financial return series where an autoregressive structure is imposed on the conditional variance. These allow the volatility shocks to persist over time and to revert to that more normal level. It also captures both the propensity of returns to cluster in time and helps explain the well-documented non-normality and non-stability of stock return distributions.

The empirical literature underlying this knowledge of stock return volatility is voluminous. Unfortunately, much of this knowledge has been garnered from just a few contexts. First, most of what we know about financial return volatility in general has been based on studies employing interday returns. Given that financial markets display high speeds of adjustment, studies based on daily (or longer) observations may fail to capture critical information contained in intraday price movements. Moreover, of that small number of studies that are concerned with intraday data, almost all addresses foreign exchange or futures market volatility [see, for instance, Baillie & Bollerslev (1990), Locke & Sayers (1993), Andersen & Bollerslev (1997), Tse (1999)] and much less in stock markets. Second, within the small intraday stock return volatility literature, most studies have concentrated on indexes or index futures contracts with less attention directed to the intraday return volatility of individual securities [see, for instance, Baillie & DeGennaro (1990), Kim & Kon (1994), Kyriacou & Sarno (1999) , Walsh & Quek (1999)]. Because it is likely that volatility effects vary across individual securities in much the same manner as they do across markets, the analysis of stock return volatility at the company level would throw light on the characteristics of volatility within a single market.

Third, the bulk of volatility modeling has been concerned with univariate characteristics such that the volatility of a return series is related only to information in its own history. As Bollerslev et al. (1992: 32) notes: "the widespread existence of ARCH effects and the persistence of stock return volatility have led researchers to search for it origin(s). [Since] the GARCH (p,q) model can be viewed as a reduced form of a more complicated dynamic structure for the time-varying conditional second-order moments…interpretations and explanatory variables for the observed ARCH effects have been proposed both on the micro and macro level…". However, while the macro level has received a good deal of attention, including the influence of other financial assets and exogenous deterministic events such as macroeconomic and company announcements on the volatility process, much less has been directed to micro level influences [for exceptions, see Lamoureux & Lastrapes (1990), Kim & Kon (1994) , Rahman et al. (2002)]. Finally, only a few ARCH-type studies of stock return volatility have been undertaken in Australia, and as far as the authors are aware, none using intraday data at the individual security level. Following Bollerslev's et al. (1992: 31) suggestion it would "…be interesting to use different data sets to further assess the degree of persistence on stock return volatility [since] with very few exceptions, most current studies use data from the US stock market".

The overall hypothesis is to assess return and volatility and relationships in fifty Australian stocks by incorporating new arrival of information namely, the inclusion of news arrival as proxied by the contemporaneous and lagged volume of trade, bid-ask spread together with day-of-week and information asymmetry effects are used as exogenous explanatory variables. These allow the estimation of volatility clustering over time, and to determine whether shocks persist over time, and/or revert to a more normal level. The outcomes of these analyses will provide useful models and forecasts for investors, funds managers and financial institutions.

Accordingly, the purpose of this paper is to investigate the intraday return volatility process in Australian stocks. The remainder of the paper is divided into four sections. The second section explains the data employed in the analysis and presents some brief summary statistics. The third section discusses the methodology employed. The results are dealt with in the fourth section. The paper ends with some brief concluding remarks.

2. Data and summary statistics

The data employed in the study consists of last price, trading volumes and bid-ask spreads for the five-minute intervals from 31 December 2002 to 4 March 2003 for the national and multinational stocks included in the S&P/ASX 50 index. The sample period is used because it is the longest period available for each of the 50 Australian stocks. The S&P/ASX 50 index comprises the fifty largest stocks by market capitalization in Australia and currently accounts for some seventy-five percent of the market capitalization of domestic equities listed on the Australian Stock Exchange (ASX). The criteria for inclusion in the index place an emphasis on liquidity and investability and together the high frequency of information arrivals and volume of trading in these securities are likely to reduce measurement error problems. All data is obtained electronically from Bloomberg. Each of the trading days in the analysis is portioned into five-minute intervals beginning with the opening of the market at 9:00 a.m. Australian Eastern Standard Time (AEST). The natural log of the relative price is computed for the five-minute intervals to produce a time series of continuously compounded five-minute returns, such that $r_t = \log(p_t/p_{t-1}) \times 100$, where p_t and p_{t-1} represent the stock price at time t and t-1, respectively. By way of comparison, Chan et al. (1995) and Rahman et al. (2002) also specified five-minute returns when modeling intraday return volatility in US listed stocks.

Table 1 presents the summary of descriptive statistics of the five-minute returns for the fifty stocks. Sample means, medians, maximums, minimums, standard deviations, skewness, kurtosis and the Jacque-Bera statistic and first-order autocorrelation coefficient and their p-values are reported. It should first be noted that over the relatively short sample period the Australian equity market generally declined, with forty-four of the stocks (eight-eight percent) producing negative mean returns. The lowest mean returns were for ALL and AMP with -0.0300 and -0.0161 percent, respectively. However, six stocks had positive average returns over this same period ranging from 0.0005 (WOW) to 0.0029 (CCL). The largest five-minute returns were for CCL (0.0209) and MBL (0.0017). The standard deviations of returns range from 0.144 (MGR) to 1.053 (ALL). On this basis, of the fifty stocks AGL, CBA, MGR, NAB, SGB and SGP are the least volatile, with ALL, SRP and MIM being the most volatile.

Mostly, the distributional properties of all fifty return series appear non-normal. Twenty-seven of the return series are negatively skewed, ranging from -0.1297 (STO) to -35.1062 (ALL), indicating the greater probability of large deceases in returns than rises. The remaining return series are positively skewed, also suggestive of volatility clustering in intraday stock returns. The asymptotic sampling distribution of skewness is normal with mean 0 and standard deviation of, where T is the sample size. Since the sample size for all the return series is 3,215 then the standard error under the null hypothesis of normality is 0.0432: all estimates of skewness are significant at the .10 level or lower. The kurtosis, or degree of excess, in all stock returns is also large, ranging from 5.6283 for MIM to1647.6950 for ALL, thereby indicating leptokurtic distributions. Given the sampling distribution of kurtosis is normal with mean 0 and standard deviation of, then all estimates are once again statistically significant at any conventional level.

The calculated Jarque-Bera statistics and corresponding p-values in Table 1 are used to test the null hypotheses that the five-minute distribution of stock returns is normally distributed. All p-values are smaller than the .01 level of significance suggesting the null hypothesis can be rejected. These stock returns are then not well approximated by the normal distribution. To test for the presence of autocorrelation in the five-minute interval series, the first order autocorrelation coefficients are also calculated and presented in Table 1 along with their corresponding p-values. The asymptotic distribution of $\hat{\rho}_1$ is normally distributed with a mean of 0 and a standard error of $1/\sqrt{3126} = 0.0176$. On this basis, first-order autocorrelation is evident in the intraday return series for the Australian stocks selected at the .05 level or lower, with the exception of CSL, QBE, RMD and WPL.

3. Model specificationN

The distributional properties of Australian company intraday stock returns indicates that generalized autoregressive conditional heteroskedastistic (GARCH) models can be used to examine the dynamics of the return volatility process. Autoregressive conditional heteroscedasticity (ARCH) models (as introduced by Engle (1982)) and generalised ARCH (GARCH) models (as presented by Bollerslev (1986)) that take into account the time-varying variances of financial time series data have already been widely employed. Suitable surveys of ARCH modeling in general and/or its widespread use in finance applications may be found in Bera and Higgins (1993) and Bollerslev et al. (1992; 1994). Pagan (1996) also contains discussion of developments in this ever-expanding literature.

The first methodological requirement is to remove the predictable component of returns so as to produce a return innovation, e_t, with a conditional mean of zero before a GARCH equation is specified for the variance. One common method to produce an uncorrelated process in the five-minute returns is to assume that the level of returns follow an AR(1) process. The following conditional expected returns equation accommodates each stock's own returns and its returns lagged one period:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + e_t \tag{1}$$

where r_t is the return for each stock in the current period and r_{t-1} an n x 1 vector of the returns lagged one period, α_0 represents the long-term drift coefficient and α_1 is the degree of mean spillover effect across time, or put differently, whether the lagged can be used to predict the current return and e_t, the random error or innovation at time t, is approximately distributed $e_t \sim N(0, h_t)$.

The second methodological requirement is to model the variance of the return innovation itself. A GARCH process of orders p and q, denoted as GARCH(p,q), for the conditional variance (volatility) of e_t at time t can then be represented as:

$$h_t = \beta_0 + \beta_i \sum_{i=1}^{p} e_{t-i}^2 + \gamma_i \sum_{i=1}^{q} h_{t-i} \tag{2}$$

where h_t is the conditional variance volatility of e_t at time t, β_0 is a constant, β_i and γ_i are coefficients that are associated with the past values of innovation and volatility spillovers to the current volatility, and thereby represent news about the degree of innovation from previous periods (ARCH terms) and previous period's forecast volatility spillover effects (GARCH terms), and all other variables are as previously defined.

One important and well-founded characteristic of stock returns is the tendency for volatility clustering to be found, such that large changes in returns are often followed by other changes, and small changes in returns are often followed by yet more small changes. The implication of such volatility clustering is that volatility shocks today will influence the expectation of volatility many periods in the future. The aggregation of β_i and γ_i coefficients measures this degree of continuity or persistence in volatility. If the degree of persistence is close to one, this implies that the current volatility of intraday returns is affected by past volatility that tends to persist over time: the actual persistence of volatility must depend on the persistence of the exogenous variables. Further, volatility clustering also implies that volatility will come and go. Accordingly, a period of high volatility in stock returns will eventually give way to a more normal (lower) level of volatility and a lower period of volatility will be replaced with a more normal (higher) level of volatility. This process of reversion to a normal or mean level of volatility implies that even if volatility persistence exists, so long as the sum of the β_i and γ_i coefficients is significantly less than one the volatility process, while having a long memory, will still be mean reverting or stationary.

A concern with the volatility generation process as defined is that current volatility is only related to the past values of innovation and volatility spillovers from previous periods. It is likely that variables other than these may contain information relevant for the volatility of stock returns and a possibility is that the incidence of time varying conditional heteroskedasticity could be due instead to an increase in the variability in returns following the arrival of new and irregular information. This is important because the GARCH effects often observed in stocks returns is likely the outcome of the stochastic properties of these factors. Lamoureux and Lastrapes (1990) and Rahman et al. (2002), for example, argue that an appealing explanation for the presence of GARCH effects is that the rate of information arrival is the stochastic mixing variable that generates stock returns. For daily, weekly and monthly data, variables such as macroeconomic and company announcements may be major influences. However, for high-frequency intraday data the variables likely to be of most influence relate to trade information.

One means of proxying the arrival of this trade information is to introduce the volume of trade into the conditional variance equation. Lamoureux and Lastrapes (1990), for example, showed that with the introduction of the contemporaneous and lagged volume of trade (indicating a greater amount of information) the GARCH effect in US stock returns became insignificant for the majority of securities, with the estimated coefficients on trade volume being significant, though small. Alternatively, Najand and Yung (1991), Foster (1995) Rahman et al. (2002) found that the GARCH effects remained strongly significant with the inclusion of the current volume of trade in the conditional variance equation. Another way of including this information arrival follows past evidence of a high correlation between intraday return volatility and intraday variation of bid-ask spreads (Copeland & Galai, 1983; Grossman & Miller, 1988; McInish & wood, 1992; Walsh & Quek, 1999 and Wang and Yau 2000). For instance, Rahman et al. (2002) introduced the bid-ask spread as a measure of information that flows into the market with the argument that bid-ask spreads narrow when information flow increases and widen when information flow decreases. In this study, day-of-week effects have also been introduced in the conditional variance equation to take account of the intraday patterns in the high frequency data. It is widely known that the stock prices tend to be higher at the beginning of the week than any other trading days.

The final methodological requirement is then to incorporate the arrival of exogenous information in the volatility return generating process in Equation (2). Since the incidence of the time varying conditional heteroskedasticity could be due to an increase in the contemporaneous and/or lagged volume of trading and/or bid-ask spread and day-of-week effects following the simultaneous arrival of new information, the conditional variance equation is reformulated as:

$$h_t = \beta_0 + \beta_1 e_{t-1}^2 + \gamma_1 h_{t-1} + \delta_1 v_t + \delta_2 v_{t-1} + \delta_3 s_t + \delta_4 s_{t-1} + \sum_{i=2}^{5} \eta_i d_i \qquad (3)$$

where v_t and v_{t-1} and s_t and s_{t-1} represent the volume of trade (v), bid-ask-spreads (s) in period t and t-1, d_i are dummy variables for each of the day-of-week effect having values of 1 for d_2 (Tuesday) and 0 otherwise,… having values of 1 for the d_5 (Friday) and 0 otherwise. To avoid the multicollinearity trap, Monday (d_1) is chosen to be the reference category for the interday effects, η_i are coefficients that are associated with the dummy variables day-of-week effects. All other variables are as previously defined.

The standard GARCH model assumes that the impact of news has a symmetric effect on volatility. Glosten et al. (1993) extends the symmetric into asymmetric GARCH also known as Threshold ARCH (TARCH) model to capture the asymmetric response of the conditional response of the volatility of news arrival. Antoniou et al. (1998) and Rahman et al. (2002) use variations of the GARCH models which incorporate for the asymptotic responses of vitality to news arrival on stock markets. The asymmetric GARCH model includes along with the standard variables, the squared values of e_{t-1} when e_{t-1} is negative.

$$h_t = \beta_0 + \beta_1 e_{t-1}^2 + \gamma_1 h_{t-1} + \tau_1 a_t e_{t-1}^2 + \delta_1 v_t + \delta_2 v_{t-1} + \delta_3 s_t + \delta_4 s_{t-1} + \sum_{i=2}^{5} \eta_i d_i \qquad (4)$$

where $a_t = 1$, if $e_{t-1} < 0$,, $a_t = 0$ otherwise.

This allows the squared residuals to have a different impact on the conditional volatility when the lagged residuals are negative than when the lagged residuals are positive. That is, it is assumed that positive news (where return changes in an upward direction and residuals are positive) alters return volatility differently to negative news (where return changes are in a downward direction and the residuals are negative).

4. Empirical results

The estimated coefficients and standard errors for the conditional mean return equations are presented in Table 2. Different GARCH(p,q) models were initially fitted to the data (results not shown) and compared on the basis of the Akaike and Schwarz Information Criteria (AIC and SIC) from which a GARCH(1,1) model was deemed most appropriate for modelling the five-minute return process for all fifty stocks. All the same, Rahman et al. (2002: 165) confined "…estimation to the GARCH(1,1) specification since it has been shown to be a parsimonious representation of conditional variance that adequately fit many high-frequency time series". For simplicity, this paper only focuses on the GARCH(1,1) and asymmetric GARCH(1,1) models with no higher orders to be estimated. Of the fifty stocks, forty-eight (ninety-six percent) exhibit a significant own mean spillover from their own lagged return with the exception of RMD and WSF at the 0.10 level of significance and lower. In all significant cases, the mean spillovers are negative. For example, and during this particular sample period, a 1.00 cent increase in MIM's own return will Granger cause a decrease of 0.36 cents in its return over the next five-minutes. Likewise, a 1.00 cent increase in returns for CSL will Granger cause a 0.05 cent decrease over the next five-minutes.

Also included in Table 2 are details for AIC and SIC comparing the performance of asymmetric GARCH(1,1) models including information arrival and day-of-week effects as exogenous variables in the variance equation with those obtained from a simple GARCH(1,1) process. These model selection criteria are used to test the proposition that the occurrence of time-dependent conditional heteroskedasticity could be due, at least in part, to an increased volume of trading and/or variability of prices following the arrival of new information in the market. In the current analysis, the arrival of new information is proxied by including trading volume and bid-ask spread, asymmetric and day-of-week effects in the variance equation.

The values for AIC and SIC in Table 2 indicate that in nine of the stocks the intraday return volatility process could be appropriately modelled employing a simple GARCH process, whereas in the remaining forty-one stocks the rate of information arrival together with the asymmetry effect have some significant role in generating intraday returns. For example, for JHX the lower values for AIC and SIC (-0.0889 and -0.0795) compared to AIC(δ) and SIC(δ) (-0.0670 and -0.0405) indicate that a GARCH model with no allowance for exogenous variables and asymmetry is a more comprehensive and parsimonious representation of the return generation process, whereas for NCP the lower values for AIC(δ) and SIC(δ) (-0.1778 and -0.1513) as compared to AIC and SIC (0.0819 and 0.0913) indicate the reverse. By way of comparison, Lamoureux and Lastrapes (1990) found that that GARCH effects found in their US actively traded securities were due to time dependencies in the process generating information flows, whereas Rahman et al. (2002) concluded that even after proxying information arrival, GARCH effects prevailed in NASDAQ stock returns. The results in Table 2 indicate that, at least for actively traded Australian stocks, there is much variation in the role of information arrival as a means of generating the commonly found GARCH effects with it having a critical role for some stocks, but not for others.

Initially a TARCH(1,1) model without news information is estimated for the fifty stocks. The ARCH effects are all significant as are the GARCH effects with the exception of ALL. The basic model is then augmented with the inclusion of contemporaneous bid-ask spread followed by the contemporaneous volume of trade. In the interests of conciseness, the results for these three models are not reported, but can be supplied on request. With the inclusion of the contemporaneous bid-ask spread in the TARCH(1,1) model, the results show that the GARCH effects remain strongly significant with the exception of GPT. Similarly, the ARCH effects also remain strongly significant with the exception of ALL. There is a significant negative relationship between the contemporaneous bid-ask spread and return volatility for twenty-six of the twenty-eight coefficients. For lagged bid-ask spread, eighteen of the twenty-two positive relationships are significant. These results indicate that the contemporaneous bid-ask spread is negatively related to return volatility but positively related to lagged bid-ask spread. Rahman et al. (2002) use a GARCH(1,1) model and find that all but eight of the thirty NASDAQ stocks exhibit a positive relationship between lagged bid-ask spread and return volatility. The significance of the positive results indicates that "…information arrival would be expected to induce an increase in volatility and this would in turn have the effect of widening the bid-ask spread" (Rahman et al. 2002). The difference appears to lie in that this study includes both contemporaneous and lagged bid-ask spread, whereas Rahman's et al. (2002) results are referenced only to lagged values.

Rahman et al. (2002) also point out that the standard GARCH model assumes that the impact of news arrival on volatility is symmetrical; with Antoniou et al. (1998) suggesting the model is misspecified if news information has an asymmetric effect on volatility. The TARCH model with the inclusion of bid-ask spread should then be more reliable for forecasting stock returns. The introduction of the contemporaneous volume of trade to the TARCH(1,1) model suggests that contemporaneous volume is positive and significantly related to return volatility for all fifty stocks. The ARCH effects remain significant and the GARCH effects are also significant with the exception of MAY, MGR and NCP. The contemporaneous volume of trade can then also be considered as an important proxy for news information.

Table 3 presents the estimated coefficients for the conditional variance equations in the TARCH model. The coefficients of the conditional variance equations are all significant at the 0.01 level or lower for the innovations and volatility spillovers for the fifty stocks indicating the presence of strong ARCH and GARCH effects. The own-innovation spillovers in all stocks are significant indicating the presence of strong ARCH effects. These own-innovation spillover effects range from 0.0143 in RIO to 0.2286 in SRP. In the GARCH set of parameters, all fifty of the estimated coefficients are also significant. The lagged volatility spillover effects range from 0.3502 for BHP to 0.7801 for AMC. This implies that the past volatility shocks in AMC have the greatest effect on its future volatility shocks than for any other stocks included in the analysis during the sample period.

The next coefficient examined is that corresponding to the asymmetric volatility response (τ_1) to positive and negative shocks such that volatility tends rise in response to 'bad news' and fall in response to 'good news'. Of the fifty stocks, thirty-one (sixty-two percent) exhibit a significant asymmetric effect at the 0.10 level of significance and lower. This follows eighteen stocks with significant asymmetric effects are negative thus observing that downward movements in the market (falling returns) are followed by higher volatility. And also, the estimated asymmetric coefficients are significant and positive for thirteen stocks indicating the reverse that positive shocks (increasing returns) are associated with higher volatility. As hypothesised by Antoniou et al. (1998) and Rahman et al. (2002) amongst others, positive news causes a different volatility response than negative news, a more comprehensive understanding of Australian intraday stock return volatility has resulted from the application of the asymmetric GARCH or Threshold ARCH (TARCH) model as first proposed by Glosten et al. (1993).

According to the TARCH process, the sum of the ARCH, GARCH and a half of the asymmetric coefficient measures the overall persistence in each market. A value of less than one indicate a mean reverting conditional volatility process in which shocks are transitory in nature. All fifty stocks display strong own persistence volatility ranging from 0.4092 for GPT to 0.8432 for AMC. Thus, AMC has the highest lead-persistence volatility spillover effect as compared to the other stocks included in the analysis. The average persistence across the stocks is 0.6472 and this implies a volatility half-life, defined as the time taken for the volatility to move halfway back towards it unconditional mean following a deviation from it, of 1.5931 periods or about 8 minutes, where. This impact decays geometrically. This implies that for many of the stocks included in the analysis volatility shocks will tend to persist over what seems only a relatively short period of time. By way of comparison, the volatility half-life for the stock with the longest lead-persistence is nearly 20 minutes and that for the shortest is just 4 minutes, while for a comparable international study Rahman et al. (2000) provided tables suggesting a mean volatility half-life of 13 minutes in a sample of NASDAQ stocks (as calculated by the authors). Other stocks that have a relatively higher level of persistence in volatility over time (and their half-lives) include AMC (0.8432 and 20 minutes), TLS (0.8351 and 19 minutes) and CCL (0.7907 and 15 minutes) while those with a lower level of persistence include GPT (0.4092 and 4 minutes), BHP (0.4132 and 4 minutes), and CSL (0.4861 and 5 minutes). Nonetheless, although the returns volatility in these stocks appears to have a quite long memory, at least in terms of high frequency data, they are still mean reverting.

Table 4 includes the estimated coefficients, standard errors and p-values for the variables used to proxy the irregular arrival of new information: namely, contemporaneous and lagged volume of trade and contemporaneous and lagged bid-ask spread. To start with, there is a significant, and almost always positive, relationship between the return volatility and the contemporaneous volume of trade for all stocks with the exception of WFA which exhibit a significant negative relationship. The contemporaneous volume of trade ranges from -0.0007 (WFA) to 0.2841 (CSL). As expected, this would indicate the increase of new information, as proxied by trade volume, is associated with an increase in return volatility. This at once lies counter to early work by Lamoureux and Lastrapes (1990) who found that the introduction of contemporaneous volume into the conditional variance equations made the GARCH effects disappear for the majority of US securities or Lee et al. (2001) who found that daily trading volume used as proxy for information arrival had no significant explanatory power for the conditional volatility of Chinese daily returns. They are, however, broadly comparable to work by Najand and Yung (1991), Foster (1995) and Rahman et al. (2002).

At the same time, thirty-five stocks have a significant relationship between return volatility and lagged volume of trade where eighteen of these stocks (some fifty-one percent) are negative. This would suggest that following the role of new information in the current period to increase return volatility; information in the lagged period has the role of reducing return volatility. This is perhaps an indication of the ability of the equity market to process high-frequency information whereby adjustments are made to over and under-reaction in the current period on the basis of historical information. Nevertheless, the magnitude of all contemporaneous and lagged volume coefficients, whether positive or negative, is relatively small, and their impact on the GARCH effect is minimal.

With the inclusion of contemporaneous bid-ask spread as yet another measure of information flow, the estimated coefficients for forty-five of the stocks (ninety percent) are significant. All of the significant coefficients indicate a negative relationship between return volatility and contemporaneous bid-ask spread with the exception of CSL, NCPD and WFA. For the most part, this would suggest that as bid-ask spreads widen (less new information) return volatility will decrease, while a narrowing of bid-ask spreads (more new information) is associated with an increase in return volatility. Forty-four stocks (eighty-eight percent) also show a significant relationship between return volatility and lagged bid-ask spread of which thirty-eight cases are positive. Interestingly, the coefficients for the contemporaneous and lagged bid-ask spreads are larger in magnitude than the coefficients for either the contemporaneous or lagged volume of trade. These results would lead us to suspect that bid-ask spread may be a more appropriate proxy for information arrival, at least for a select number of stocks. However, information arrival as proxied by the volume of trade is spread across almost all of the stocks, indicating the information proxied by the volume of trade is more general than specific than that provided by bid-ask spread. Moreover, the fact that most of the estimated coefficients are significant indicates that the simultaneity problem between prices, volume and bid-ask spread though present, is not too serious.

The coefficients included in Table 5are those corresponding to the variables used to proxy the arrival of new information such as the day-of-week (η_i) effects. Of the fifty stocks, forty-three (eighty-six percent) exhibit a significant relationship between return volatility and Tuesday and Friday as new information arrival and in addition forty-five (ninety percent) are also significant for Wednesday and Thursday. Volatility in thirty-six (seventy-two percent) of the stocks is highest on Monday and falls progressively through the week. Volatility is lowest on Thursday for AMP, Tuesday for IAG and Wednesday for PBL. The day-of week effects are significant for WFT with Friday having the highest and Tuesday the lowest volatility.

5. Concluding remarks

This study presents an analysis of the distributional and time-series properties of intraday returns in the Australian equity markets. The data employed for this study consists of five-minute returns for the large capitalization, high liquidity stocks comprising the S&P/ASX 50 stock index over the period 31 December 2002 to 4 March 2003. The results indicate that intraday return volatility in the Australian market is best described by an asymmetric GARCH(1,1) specification and that the inclusion of the contemporaneous and lagged volume of trade and bid-ask spread and day-of-week effects in the conditional variance equations account, at least in part, for some of the GARCH effects observed in stock returns. However, the GARCH effects remain strongly significant for all securities even after the introduction of trade volume and bid-ask spreads and day-of week effects as proxies for the irregular arrival of new information, suggesting that the GARCH effects commonly found in security returns are not solely due to time dependence in the process generating information flows.

The most important result of this study is that there is much variation in the time-series properties among the stocks included in the sample, despite the fact that they are drawn from a relatively homogenous subset of the Australian equity market. While all of the stocks exhibit the volatility clustering and predictability expected in intraday equity returns, the persistence of this volatility varies markedly with half-lives anywhere between four and twenty minutes. Likewise, the role of trading volume, bid-ask spreads and day-of-week effects as proxies for information arrival in producing these volatility effects also varies, with the effect of contemporaneous and lagged volume being general but relatively small, while the influence of contemporaneous and lagged bid-ask is relatively larger but more specific. Nonetheless, though the degree of volatility clustering and its persistence varies across the sample, in all of the stocks it is nonetheless mean-reverting, indicating that after departure to some higher or lower level of volatility there will be an eventual return to some more normal level.

In sum, based on the AIC and SC criteria, the asymmetric GARCH (1,1) model including information arrival as exogenous variables in the variance equation out performed those obtained from a simple GARCH(1,1). The TARCH process can be used to capture the occurrence of time-dependent conditional heteroskedasticity including the volume of trade and/or variability of prices following the arrival of new information in the market. The arrival of new information proxied by including trading volume and bid-ask spread and day-of-week effects is highly significant in examining the volatility dynamics of Australian stocks. Evidence to date suggests stock returns can vary according to the day-of-week and various market conditions. Whether this increased volatility persists is a matter of interest to market participants who heavily rely on a complete and up-to-date knowledge of stock return risk, therefore it is important to be able to assess return and volatility relationships in the Australian stock market.

Of course, there are several ways in which this work could be extended, especially considering the dearth of literature concerning intraday returns and/or volatility in the Australian equity markets at the micro level. One possibility is to examine the behaviour of return volatility during the day following some US evidence that volatility is high at the open, close of trading, and low in the middle of the day (Bollerslev et al. 1992). Another is to use intraday data in conjunction with daily and weekly data to examine the role sampling frequency has on the observed significance of GARCH effects in stock level data. While it is generally thought that GARCH effects are less common as sampling frequency falls, there is nothing in the equity literature, in Australia or elsewhere, that parallels Andersen's and Bollerslev's (1997) wide-ranging analysis of the influence of sampling frequency in foreign exchange markets.

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