An analysis of intraday market behaviour before takeover announcements

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Abstract

The objective of this study was to analyse the changes in the intraday market microstructure behaviour before a takeover announcement for a sample of target, bidder and control (non-target) companies. Under the hypothesis that agents with asymmetric information were operating in the market, the Autoregressive Conditional Duration (ACD) model was used to estimate the joint impact of duration and microstructure variables on the returns volatility in the months before the event. The analysis was conducted on tick-by-tick data over a period of six to four months, and then three months before an announcement date. Our results suggested that the effect of information on the returns volatility, as measured by several economic and intraday microstructure observable variables, was different between target, bidder and non-target companies leading up to the takeover announcement. These variables were durations between trades, the surprise in durations, spreads and trading volumes. It was concluded that the intraday trading behaviour for takeover targets was affected by traders who held private information (especially the bidders) at least three months before the official announcement of the offer. The selected stocks were traded on the Australian Stock Exchange (ASX) and were sourced between 2004 and 2008 from a wide range of industries and with different levels of liquidity.

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1. Introduction

Research in financial market microstructure has advanced several hypotheses and conclusions concerning information flows in traded markets. For example, the periods of time in which no trades occur were considered by Diamond and Verrecchia (1987) as periods where the information revealed to the market was not of the type that encouraged trading. On the other hand, Easley and O'Hara (1992) developed a plausible theory which proposed that a lack of trades meant ‘no’ news in the market. While microstructure models generally assume informational asymmetries among investors, a takeover announcement reveals information unknown to most market participants. The arrival of this information has a positive effect on the price of the target firm. It gives informed investors with privileged information a strong incentive to trade on their information prior to the takeover announcement. In many cases, understanding trading volatility is important for identifying informed investors. In the case of a takeover announcement, they can include companies involved in negotiations, or third parties that have specific knowledge of the planned offer.

A number of studies have approached the firm acquisition and agent behaviour around an event using variables such as spread, market depth, return volatility and volume traded (for example, see Conrad and Niden (1992), Foster and Viswanathan (1995), Smith, White, Robinson, and Nason (1997), Jabbour, Jalilvand, and Switzer (2000), Farinos, Garcia, and Ibáñez (2002) and Marshall (2006)). The contribution made by individual economic and microstructure variables to volatility within the trading environments of actual takeover targets prior to an announcement creates information patterns that are consistent across a large number of targets. It is hypothesised that these patterns may help in the identification of future targets.

As active mergers and acquisitions markets expand, opportunities increase for the profitable use of information through trading in anticipation of bids. Strong evidence of the nature of corporate events has been gathered from high-frequency data analysis in previous studies. The use of microstructure techniques to decompose the bid-ask spread and price impact into patterns based on information components has allowed more precise perceptions regarding asymmetric information over time. Frino and Wearing (2005) found in their study that intraday patterns were relevant for identifying when
profitable trading opportunities were likely to appear. Further, \textit{Easley and O’Hara} (1987) developed an alternative explanation for the price–quantity relationship by showing that quantity is important due to its correlation with private information related to the security’s true value. In particular, they suggested that adverse selection problems arose due to the preference of informed traders to trade larger amounts at any given price. While Foster and Viswanathan (1990) found that bid-ask spreads are elevated as many as seven days before the date of an announcement, Jennings (1994) supported the contrarian view that there was little evidence related to spread increases before announcements. He did, however, support the idea that there is some anticipated intraday trading activity before takeover announcements.

Under the assumption that agents with asymmetric information were operating in the market, this study aims to describe how the intraday market was affected by the release of private information before a takeover event. This description incorporated the search for intraday trading variables and patterns that revealed information prior to a takeover offer announcement being made public. More specifically, the trading behaviour of targets and bidders was studied to determine how economic and market microstructure variables were affected by the event.

To our knowledge, this is one of relatively few studies to directly analyse the high-frequency trading environment before a takeover announcement and, in doing so, to use the ACD model to answer a finance-related question concerning the merger and acquisition market. In order to achieve generalized results, this study extends previous research by analysing a wide range of companies that comprise firms of varying sizes, levels of liquidity and industries. The results from modelling a large number of companies using the basic ACD model specification were compared by observing the evolution of model parameters over time and among groups of target, bidders and non-targets.

In the following section of the paper, duration and the modelling of high frequency market microstructure data are discussed. The data analysis is developed in Section 3, with the results of the estimation of the ACD model reported in Section 4. The conclusions are contained in Section 5.

2. Duration and the modelling of high frequency market microstructure data

Most financial market studies in the past have relied upon the collection of data at discrete and equally spaced points in time. The use of data that is discretized according to calendar time may not be synchronous with events or information flows and may, therefore, lead to the erroneous measurement of variables such as volatility. Data in calendar time formed the basis for the majority of previous market-microstructure studies. This was partly due to the limited availability of high-frequency data in the past, along with the prevailing view that information shocks to a market were unlikely, or indeed improbable, over extremely short time frames.

Rather than relying on discretely sampled data, or the aggregation of data at fixed intervals, each transaction for the period was incorporated into the analysis. This included consideration of all the trades, as well as variables associated with those trades that conformed to the theoretical underpinnings of the market-microstructure literature. The use of high-frequency data allowed the analysis of the statistical nature of information in real time, along with the addition of important explanatory variables for the information process such as the duration between trades.

2.1. A financial point process

High frequency data is by definition irregularly spaced in time and is known statistically as a point process. It follows a stochastic process that generates a random accumulation of points along the time axis. In the case of high frequency financial data, the timing of the trades on listed stocks is viewed as a point process with the associated characteristics of such data known as marks. These marks include microstructure variables, such as transaction volumes and quoted bid-ask spreads, and other established covariates known to influence trade duration. In financial markets, a marked point process refers to the time of a trade and its corresponding marks. This kind of process was used by \textit{Engle} (2000) as a framework for the analysis of the trading process.

Microstructure research using tick-by-tick data calls for an alternative approach to time series analysis by consideration of a process marked at uneven points in time. In this study the length of time between consecutive observations, or durations, is used to examine the information process. Let \( \{ t_0, t_1, \ldots, t_n, \ldots \} \) be the times of the sequence of trades of an asset traded on a financial market where \( 0 = t_0 \leq t_1 \leq \ldots \leq t_n \leq \ldots \leq t_{N(T)} = T \), and let \( \{ z_0, z_1, \ldots, z_n, \ldots, z_{N(T)} \} \) be the sequence of marks corresponding to the arrival times of trades. Duration is defined as \( x_i = t_i - t_{i-1} \), where \( x_i \) is the \( i \)-th duration between trades that occur at consecutive times \( t_i \) and \( t_{i-1} \). If \( t_{i-1} \) is the information set available at time \( t_{i-1} \), then included in this set are past durations of financial trades and pre-determined marks. According to \textit{Engle} (2000), it is the joint sequence of durations and marks, given by \( \{(x_i,z_i), i=1, \ldots, T \} \) that should be modelled.

2.2. The Autoregressive Conditional Duration (ACD) model

The use of irregularly spaced data questioned the use of standard time series models and called for an ACD-type model. \textit{Engle and Russell} (1998) introduced a marginal duration model called the Autoregressive Conditional Duration (ACD) model. They defined the conditional expected duration, \( \psi_i \), as:

\[
\psi_i = E(x_i | I_{i-1}) = \psi_i(x_{i-1}, \tilde{z}_{i-1}; \theta),
\]

(1)

where the \( \theta \)'s are parameters.

A multiplicative error structure was assumed with \( x_i = \psi_i \epsilon_i \) and the standardized durations, \( \epsilon_i \), assumed to be independent and identically distributed (i.i.d.). Then:

\[
E(x_i) = E(\psi_i \epsilon_i) = \psi_i E(\epsilon_i) = \psi_i, \text{ and } E(\epsilon_i) = 1.
\]

(2)

The standard ACD model of \textit{Engle and Russell} (1998) relied on a linear parameterisation of Eq. (1), with expected duration expressed as an autoregressive equation of previous and expected durations, and specified below in Eq. (3).

\[
\psi_i = \omega + \alpha x_{i-1} + \beta \psi_{i-1}
\]

(3)

The restrictions \( \alpha \geq 0, \beta > 0 \) and \( \alpha + \beta < 1 \) ensured the existence of an unconditional expected duration and that durations were stationary and positive.

\textit{Engle} (2000) argued that a volatility model in tick time was based on the decomposition of the density function of the sequence of durations and marks. Accordingly, he provided a suitable framework for the joint modelling of durations between events of interest, \( x_0 \), and market characteristics, \( z_0 \). Price return volatility is usually measured over fixed equally spaced time intervals. However, the volatility of asset prices over short between-trade intervals is likely to be different from volatility over a longer duration. To account for differences in asset price volatility corresponding to different duration between trades, and how these differences are affected by influential covariates or marks, \textit{Engle} (2000) introduced the ACD-GARCH model. It was based on an ACD model of the type defined in Eqs. (1) to (3) and used to describe duration conditioned on the past information set. Additionally, the variance of returns was
modelled by a GARCH model adapted for irregularly time-spaced data and, as a result, volatility was measured per unit of time by conditioning on contemporary and past durations. Assuming the property that durations are weakly exogenous, the ACD model was estimated first. Volatility of returns was then estimated from the GARCH model using expected and contemporaneous duration estimates from the first stage, along with selected covariates or marks.4

As in Engle (2000), the return per unit of time, \( \frac{r_i}{\sqrt{X_i}} \), was modelled as an ARMA(1, 1) process that was conditioned on duration. It followed that:

\[
\frac{r_i}{\sqrt{X_i}} = \rho \frac{r_{i-1}}{\sqrt{X_{i-1}}} + \varepsilon_i + \phi \varepsilon_{i-1},
\]

where, \( r_i \) was the return and the innovation term was given by \( \varepsilon_i \).

The variance of returns was conditioned on the contemporarily time-spaced data and, in order to adapt for irreguarly time-spaced data. Accordingly, the variance per unit of time, \( \sigma_i^2 \), became:

\[
\sigma_i^2 = V \left( \frac{r_i}{\sqrt{X_i}} \right).
\]

Following this transformation, the GARCH (1, 1) model was used to model return volatility as a variable dependent upon both economic time and activity. The basic variance equation for the process was given by:

\[
\sigma_i^2 = \gamma_1 + \gamma_2 \varepsilon_{i-1}^2 + \gamma_3 \sigma_{i-1}^2,
\]

where \( \gamma_1 > 0, \gamma_2 \geq 0, \gamma_3 \geq 0, \gamma_3 < 1 \).

In order to provide greater support for any of the published theories regarding how informed trading can be disclosed by the trading process, the basic model given by Eq. (6) was extended to offer extra explanatory power and provide a better understanding of how individual variables affected volatility. Additional duration and market microstructure variables were appended to the model with the intention of jointly evaluating their impact. This approach has been successfully used in many previous studies (see Engle (2000), Bauwens and Giot (2000) and Wong, Tan, and Tian (2009)). By including these new variables into the ACD framework, the conditional return variance was given by:

\[
\sigma_i^2 = \gamma_1 + \gamma_2 \varepsilon_{i-1}^2 + \gamma_3 \sigma_{i-1}^2 + \gamma_4 \chi_{-1}^2 + \gamma_5 \chi_i \psi_i - 1 + \gamma_6 \psi_{i-1} + \gamma_7 \psi_i (7)
\]

Assuming that durations and volatility can be driven by the same news events, the coefficient \( \gamma_4 \) in Eq. (7) provided some indication of the effects that duration had on the current period’s volatility. If the theory of Easley and O’Hara (1992) is empirically verifiable, then short durations that follow an information event would increase volatility and \( \gamma_4 \) would be expected to be significant and positive. As duration was entered as a reciprocal, then a longer duration indicated no news, had shorter reciprocal values and had a reduced impact on volatility.

A measure of the surprise in durations, \( \frac{X_i}{\psi_i} \), adopted from Engle (2000), was also tested in the model. A positive surprise was where the actual duration was greater than expected and, therefore, \( \frac{X_i}{\psi_i} \) was greater than unity. When \( \frac{X_i}{\psi_i} \) was less than unity, then the surprise was negative. As long as the coefficient of the surprise variable, \( \frac{X_i}{\psi_i} \), is negative, then a positive surprise indicated a reduced impact on volatility relative to that of a negative surprise.

Market microstructure variables were also added to the model in Eq. (7). In much of the earlier literature, the spread was the focus of attention and took the role of the dependent variable. In this study the lagged bid-ask spread, \( \psi_{i-1} \), played a secondary role to the return process and had an interaction with duration and, in doing so, acted as an indicator of information. Following Easley and O’Hara (1992), a long duration between trades meant that no new information had been released to the market and, as a consequence, there was expected to be a correspondingly low level of trading and volatility. However, this is a situation where bidders were likely to choose to buy stock in a potential target. With this informed trading the spread would be anticipated to narrow. A negative spread coefficient for a target company was implied as a result of this market information release and a corresponding increased level of informed trading. The second microstructure variable added to the model was the contemporaneous volume-of-trades \( \psi_i \). The relation between this variable and volatility has been often studied in the literature with a positive relation the expectation. The third and fourth additions were the bid price and the number of buyers, namely \( \beta_i \) and \( \psi_i \), respectively. The reasoning behind the inclusion of these variables was to capture some influence from the buyer side of the market as part of the explanation of volatility. Both these variables were expected to have positive coefficients. Once information concerning the bidder’s intention was absorbed by the market, greater trading volume, volatility, shorter durations and narrower spreads were expected.

Also incorporated into the specification above was a variable measuring short-run volatility \( \xi_i \). This parameter directly identified the degree of persistence in the model. Assuming that volatility is not a process with long memory, the measure of short-run volatility was computed by exponentially smoothing the series, \( \frac{r_i^2}{X_i} \), with a smoothing parameter equal to 0.5.5

2.3. The hazard function

In survival analysis the hazard function, \( \lambda(t) \), is defined as the failure rate per unit of time, or the number of failures divided by the number of individuals at risk at that unit of time. This concept can be applied with success to duration analysis when considering the hazard as a function of the baseline hazard function, \( \lambda_0(t) \), that measures the instantaneous rate of arrival of the next trade based on the history of durations and the magnitude of the expected duration, \( \psi_i \). The hazard is derived by multiplying the baseline hazard function by the reciprocal of the expected duration, \( \frac{1}{\psi_i} \). By incorporating the counting process, \( N(t) \), that refers to the number of trades (event arrivals) that have occurred at, or prior to time \( t \), the derived hazard rate function can be expressed as:

\[
\lambda(t, \tilde{x}_{i-1}, \tilde{z}_{i-1}; \psi_i) = \frac{1}{\psi_{i(t)}} \lambda_0 \left( \frac{X_{N(t)} \tilde{z}_{i(t)}^2}{\psi_{i(t)}}, \psi_i \right)
\]
Because $\psi$ enters the hazard function as its reciprocal, and with duration measured in economic or transactions time, the hazard will be accelerated by a factor that depends on the magnitude of the expected duration. The smaller the expected duration, the faster is the acceleration of economic time relative to calendar time. As a consequence, Eq. (8) has been described as an accelerated failure time model in Engle (2000). Once the baseline hazard function is estimated non-parametrically using a Kaplan-Meier estimator, then Eq. (9) is used to estimate the hazard for a particular arrival. That is:

$$\hat{\lambda}_i(t) = \frac{1}{\psi_i} \left( \frac{t_{i-1} - \psi_i}{\psi_i} \right) \text{ for } t_{i-1} \leq t < t_i$$  \hfill (9)

### 3. Modelling

#### 3.1. Data statistics

A selected sample of stocks that represented the broader Australian economy was used to describe the generalized trading behaviour prior to a takeover announcement on the Australian Stock Exchange (ASX) equity market. The sample initially included the takeover target companies between 2004 and 2008 in the takeover target group. Related bidding companies were also included in the sample separately in the bidder group. Additionally, a non-target (control) company that did not experience an acquisition offer was aligned with each target to form the control group. The data was obtained from the Securities Research Centre of Australia (SIRCA) and consisted of six months of intra-day financial data for each selected ASX listed company.

The steps to define an appropriate sample of companies were as follows. First was the definition of the period. The years from 2004 to 2008 inclusive were chosen because it was a period that captured market activity leading up to the peak, as well as reflecting the market adjustments made as the economy moved towards the bottom of the cycle. Not surprisingly, after reaching the highest number of announcements for a year in 2006, the annual records fell towards 2008 with the onset of the Global Financial Crisis.

The second step was the sample definition. All companies that experienced a takeover announcement in the Australian market, along with bidders, were considered for inclusion in the sample. However, several conditions were imposed that determined the membership of the target company in the final sample. They were:

(i) The target companies selected must have been the target of a takeover announcement at any time between 01/01/2004 and 31/12/2008.
(ii) The target firms needed stock market data available in the period that comprised 180 days before the event (announcement) day in order to allow for comparisons between time periods.
(iii) No other contaminating events existed in the five trading days prior to the announcement day that could have affected the target firm price, such as dividend payments, equity issues or stock splits.
(iv) No other takeover announcement had taken place on a target firm, either as a bidder or as a target in the 180 days before the event day.
(v) The target company was required to have had enough trades in the period to allow for a consistent and efficient estimation of the model's parameters. Table 1 below details the breakdown of the totals for each year among the targets, bidders and controls.

The final number of takeover target companies included in the sample was two hundred and twenty eight (228). The target companies were the focus of this study because they represented the companies that received the acquisition offer independent of whether it was successful or not, and whether it was treated as friendly or hostile.6

One hundred and thirty five (135) bidder7 companies related to the targets were included with the purpose of extending the analysis and offering a more complete study of market behaviour. Their trading behaviour leading up to the announcement of their bids was also of interest. Additionally, a control group of two hundred and seven (207) companies8 was added to the sample to ensure that the changes in the target’s behaviour had no relation with its industry or the market as a whole. The control sample was formed by selecting companies from the same industry with approximately the same market value9 as companies in the target group. Selecting the control companies in this way ensured that the observed changes in the trading behaviour of the target was not simply the result of a systematic shock. This increased the total number of companies analysed to 570.

The sampling period comprised the six months prior to the takeover announcement made on the target company. This was later divided into two sub-samples of three months for a more detailed analysis.10 The Sample A period comprised the period from six to four months before the takeover announcement and the Sample B period contained the data for the three months before the event announcement. It was assumed that Sample A showed ordinary trading behaviour for each company, while Sample B reflected the information-related changes in the intraday trading activity related to the announcement.

A set of typical companies (target, bidder and control) were chosen to demonstrate the changes in the intraday trading behaviour among the three groups of companies. These typical companies came from the utilities industry and were represented by the target company Alinta (ALN), the bidding company Australian Gas Light (AGL) and the control company Planet Gas (PGS). Data for each of these companies included all trades and quotes for both sample periods, with the summary statistics reported in Table 2. The duration between trades, the returns and the spread are listed in columns one to three, while volume of trades, the price, the bid and ask prices and the number of bidders (buyers) make up the remainder of the table. In Table 2, duration corresponded to the specific time difference between trades with precision of $10^{-5}$ of a second. The price variable referred to the volume weighted average price of the trade. The bid price consisted of the best buy offer on the market at the time of the

## Table 1

<table>
<thead>
<tr>
<th>Year</th>
<th>ASX market targets (announcements)</th>
<th>Sample of companies</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Targets (announcements)</td>
<td>Bidders</td>
</tr>
<tr>
<td>2004</td>
<td>74</td>
<td>43</td>
</tr>
<tr>
<td>2005</td>
<td>61</td>
<td>32</td>
</tr>
<tr>
<td>2006</td>
<td>114</td>
<td>59</td>
</tr>
<tr>
<td>2007</td>
<td>119</td>
<td>55</td>
</tr>
<tr>
<td>2008</td>
<td>77</td>
<td>39</td>
</tr>
<tr>
<td>Total</td>
<td>228</td>
<td>135</td>
</tr>
</tbody>
</table>

6 As an ex-ante analysis, we assume that these outcomes will not affect the information leading to the announcement.
7 Unfortunately, not all bidders were listed on the ASX at the time of the takeover announcement, forcing many of them to be excluded from the analysis.
8 Again not all potential control companies were traded across the same six month period preceding the takeover announcement.
9 All companies for each specific target's industry at the time of the announcement were sorted and the selected control was the company with the smallest absolute difference in market value (positive or negative) to the target's value.
10 This three months' window was arbitrarily set based on findings in the literature that report changes in the market for up to 90 days before the official bid.
trade and the ask price represented the best sell offer in the system. The variable was the count of the number of shares involved in each trade. The spread variable was computed by subtracting the best bid price from the ask quotes. The last variable in Table 2 was the number of buyers in each trade. The spread variable was computed by subtracting the ask price and the best bid offer in the system.

Typical companies' summary statistics.

Table 2

<table>
<thead>
<tr>
<th>Mean</th>
<th>71.3489</th>
<th>9.23E−08</th>
<th>0.0013</th>
<th>1412.9</th>
<th>10.969</th>
<th>10.962</th>
<th>10.976</th>
<th>2.6694</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>1734.4</td>
<td>0.041199</td>
<td>0.0176</td>
<td>2E+06</td>
<td>12.34</td>
<td>12.34</td>
<td>12.35</td>
<td>20</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.00101</td>
<td>−0.03216</td>
<td>−0.347</td>
<td>1</td>
<td>10.02</td>
<td>10.01</td>
<td>7.87</td>
<td>1</td>
</tr>
<tr>
<td>Variance</td>
<td>12.31219</td>
<td>2.07E−06</td>
<td>2E−05</td>
<td>2E+08</td>
<td>0.138</td>
<td>0.1381</td>
<td>0.139</td>
<td>3.7132</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>22.6335</td>
<td>144.1262</td>
<td>6026.1</td>
<td>14.284</td>
<td>4.5528</td>
<td>4.5488</td>
<td>5.0013</td>
<td>8.4654</td>
</tr>
</tbody>
</table>

Table 2 contains two-sample t-test results for the mean comparison between the Sample A and B periods for each of the variables in the set of typical companies. From the sub-table for the target company, ALN, it was possible to observe a statistically significant decrease for the duration, spread and number of buyers, as well as a higher average volume traded. These results do not reject the assumption that there was more activity in the Sample B period, possibly induced by new information associated with a smaller average number of buyers who originated more trades with higher volume. Although the changes in the statistics for the bidder, AGL, were not as marked as those of the target company, it was possible to observe an upward change in the average volume traded and the settlement price variables, as well as a decrease in duration and spreads from the Sample A to the Sample B periods. The sub-table for the typical control company, PCS, did show changes in most averages, but in a different direction as hypothesised and not to the same degree compared to the target and bidder companies. For example, a longer duration was observed, along with a reduction in the volume per trade. These movements were assumed to not to be related to a takeover event.

While recognizing what constituted the statistics in Table 2 were the results for a typical set of companies, it is interesting to note that from the Sample A period to the Sample B period the mean duration per trade showed a statistically significant decrease for the target and the bidder, while it increased for the control company. Positive changes in the volume of trades were only significant for the target and bidder companies. Furthermore, there was a statistically significant reduction in the average spread for the target company as a result of the lower bid and ask prices. This result is consistent with the assumption of Admati and Pfleiderer (1988), among others, who postulated a negative relation between spread and trading activity, given here by the volume of trades.

3.2. Typical company hazard rates

The hazard functions for the three typical companies were estimated from the filtered trades summarized in the previous section. In order to analyse the impact of information release on
trading activity, the estimated hazard functions for the typical target, bidder and control companies across both samples are diagrammatically represented in Fig. 1 below.

The hazard rate defines the instantaneous rate of change of the next trade at time \( t \), conditional upon no trade until time \( t \), and is often viewed as the “instantaneous probability” of leaving the current state. What can be observed in Fig. 1 is the rise in the level of the hazard function from the Sample A to the Sample B periods for the target company, ALN. The higher hazard rate in Sample B and the rapid enlargement of the gap between the two samples’ hazards is further confirmation of increased trading activity in the Sample B period. In contrast, the hazard function for the bidder, AGL, showed little difference in trading intensity from the Sample A to the Sample B periods, as did its non-event related industry pair (control).

For the target company, ALN, the target hazard rate for both sample periods was the trade characteristic most affected by the upcoming takeover announcement date. By comparing all three hazard rates in Fig. 1, it can be seen that the changes experienced by the target company had little relation to market or industry related movements as indicated by the control company, PCS. This result is supportive of the findings of Lunde (1999), Bauwens and Veredas (1999) and Grammig and Maurer (2000), who also found positive correlation between hazard rates and duration.

3.3. Intraday trade characteristics

High frequency data generally has a few special characteristics that need to be addressed before estimating models. To ensure accurate modelling, the data was filtered to remove unnecessary and erroneous observations. Opening and overnight trades were removed from the sample. Any trade with a negative duration was discarded. Trades at the same time (with identical time stamp) were aggregated into one observation. The Australian market is characterised by similar intraday trading patterns and characteristics as other stock markets. These patterns have emerged from the mean average value of economic and microstructure variables at each point in time across the daily trading period.

The graphs of the intraday duration, returns and volume variables for the typical companies are characterised in Fig. 2, with the time in seconds from midnight represented along the horizontal axis.

The more pronounced intraday characteristic was the inverse V-shape from the duration graphs for the typical target and bidder companies, with periods of more active trading at the beginning and at the end of the session, and longer durations in the middle of the day. This inverse V-shaped pattern was less pronounced for the typical control company. Of note was the higher volatility during the first hours of trading for the return graphs for the three companies. Another important characteristic was the smaller volume traded in the target company in the middle of the day. These patterns are typical during the trading day and have been attributed in many studies to effects that vary from the lunch-time break to more variability at the beginning of the trading session caused by the arrival of overnight information.

From Fig. 2, the higher level of trading activity in the typical takeover target in the later period was indicated by volume traded and the duration between trades. This suggests that more information related to the takeover announcement was present in the market during the Sample B period. The control company, which had no relation to takeover involvement, did not exhibit similar patterns. This gives the impression that changes in trading activity in the target had virtually no relation to the general market or industry trading environment. Not only did this not reject the hypothesis of higher diffusion of private information in the months just prior to the announcement, at least in the cases of these typical companies, it showed that this diffusion can be captured by analysing the changes in intraday trading behaviour. These results are consistent with the assumption of the leakage of private information before takeover announcements being revealed through trading activity.

3.4. ACD model results — typical companies

Following both Engle and Russell (1998) and Engle (2000), the data was diurnally adjusted to remove any intraday seasonality that was likely to distort the estimation results. An assumption underlying the adjustment process made by Engle and Russell (1998) was that the intraday durations, \( x_t \), can be multiplicatively decomposed into a

\[ 11 \text{ Negative duration is an anomaly in the data as it would imply that the data was out of order, and was generally restricted to overnight trades.} \\
12 \text{ The trade volumes were summed and the volume weighted average price was adopted.} \\
13 \text{ This is in accordance with other studies (see Bauwens and Veredas (1999) and Grammig and Maurer (2000)).} \\
14 \text{ The averages in time were calculated through a piecewise-linear splice with 30 min interval, more fully explained in the next section.} \\
15 \text{ Where 36000 seconds represents 10 a.m. and 57600 seconds is 4 p.m.} \]
deterministic time-of-day (seasonal) component at time $t_i, \varphi(t_i - 1)$, and a stochastic counterpart $x_i$ that captured the dynamics of the durations such that $x_i = \varphi(t_i - 1)$. A piecewise-linear spline regression was fitted to the trades of all stocks during trading hours with 12 knots, each representing half hour of trading (from 10 a.m. to 4 p.m.). Effectively, the durations were regressed on the time-of-day, with the diurnally adjusted durations obtained by taking ratios of the durations to their fitted values. Following the adjustment process, the autocorrelation in the data was substantially reduced. While the seasonal adjustment process does not affect the main properties of durations, some authors have noted the need for further investigation to better understand its impact (see Meitz & Teräsvirta, 2006).

This process was mandated following the analysis of the trading patterns in the previous section that exhibited intra-daily seasonality with higher trading activity at the beginning and the end of the trading day (shorter durations), and longer durations corresponding to slower activity outside these periods. These trading patterns were regarded as characteristic features of the exchange itself, as well as the behaviour of traders who, for example, trade on overnight information at the start of trading and close their positions at the finish (see Bauwens, 2006).

The information-based model given by Eq. (7) was estimated using the method of maximum likelihood. It endeavoured to explain the complex relationship existing between information and observable economic and microstructure variables. The estimation of the volatility model built in transaction time for each of the typical companies is presented in Table 3 below.

All GARCH coefficients for each of the typical companies and across both sample periods in Table 3 (that is, coefficients $\text{RESID}(-1)^2$ and $\text{RESID}(0)^2$).

Alternative procedures have been applied by others in the literature. They include the use of cubic splines by Engle and Russell (1998) and Bauwens and Giot (2000), quadratic functions and indicator variables by Tsay (2002) and Drost and Werker (2004), while Dufour and Engle (2000) include diurnal dummy variables in a vector autoregressive system.

Not only was this process applied to the durations between trades, but it was also applied to the other market-microstructure variables analysed in this paper, namely, bid-ask spreads, returns, and average trade size.

The choice of the method of maximum likelihood was based on its versatility to deal with different models and types of data, and also due to its robustness to estimate consistent and efficient estimators.
The sign of the coefficient from the estimated models of the three typical companies were significant. This confirmed the suitability of the basic model as an appropriate specification for modelling of this data set. Changes in the number of significant coefficients from the estimated models of the three typical companies demonstrated the impact on the trading of each company across the two sample periods. An increase in the number of significant coefficients for the duration variables (1/DUR and DUR/EDUR), the spread and the volume variables (SPREADS(−1) and VOL) showed significant differences across target and bidder companies and sample periods. A consistent pattern emerged from the trading in the target companies that suggested that the duration variables, along with the two market microstructure variables, contained information of an impending takeover offer. Significant changes in the proportions of significant model coefficients for the duration variables (1/DUR and DUR/EDUR), the spread and the volume variables (SPREADS(−1) and VOL) are clearly observed in Table 4 from the Sample A to the Sample B periods. The conclusions drawn from these patterns are that the trading on the target companies is reflecting the higher information content before the announcement, and the informed trading in the targets started at least three months prior to the announcement. This illustrated how volatility and the higher trading intensity in the target companies were revealed by information released to the market from informed trading that possibly commenced in the Sample A period and continued into the Sample B period. Further, by monitoring the change in the pattern of these covariates for a potential target, it is postulated that information is revealed concerning a forthcoming takeover announcement.

While the trading activity in the bidding companies suggested that there were significant changes in the percentages of significant model

Table 3
Typical companies' estimation results for Eq. (7).

<table>
<thead>
<tr>
<th></th>
<th>Target A</th>
<th></th>
<th>Target B</th>
<th></th>
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<td></td>
<td>Variance equation</td>
<td>Coefficient</td>
<td>Std. error</td>
<td>z-Statistic</td>
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<tr>
<td>C</td>
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<td>RESID(−1)^2</td>
<td>0.120</td>
<td>0.016</td>
<td>7.322</td>
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</tr>
<tr>
<td>GARCH(−1)</td>
<td>0.592</td>
<td>0.029</td>
<td>20.412</td>
<td>0</td>
</tr>
<tr>
<td>1/DUR</td>
<td>0.688</td>
<td>0.079</td>
<td>8.695</td>
<td>0</td>
</tr>
<tr>
<td>DUR/EDUR</td>
<td>−0.008</td>
<td>1.585</td>
<td>−0.005</td>
<td>0.996</td>
</tr>
<tr>
<td>SPREADS(−1)</td>
<td>−0.002</td>
<td>0.044</td>
<td>−0.038</td>
<td>0.97</td>
</tr>
<tr>
<td>VOL</td>
<td>0.000</td>
<td>0.000</td>
<td>85.442</td>
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<tr>
<td>BIDS</td>
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<td>0.000</td>
<td>0.772</td>
<td>0.4402</td>
</tr>
<tr>
<td>SHORTVOL</td>
<td>0.001</td>
<td>0.006</td>
<td>0.109</td>
<td>0.9133</td>
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<tr>
<td>NBUY</td>
<td>0.018</td>
<td>0.257</td>
<td>0.070</td>
<td>0.9445</td>
</tr>
<tr>
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</tr>
<tr>
<td>Bidder A</td>
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</tr>
<tr>
<td>C</td>
<td>13.498</td>
<td>1.106</td>
<td>12.205</td>
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</tr>
<tr>
<td>RESID(−1)^2</td>
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<td>0.003</td>
<td>20.639</td>
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<tr>
<td>GARCH(−1)</td>
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<td>0.007</td>
<td>98.914</td>
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<tr>
<td>1/DUR</td>
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<td>DUR/EDUR</td>
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<td>−61.825</td>
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<td>VOL</td>
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<td>0.000</td>
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<tr>
<td>BIDS</td>
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<td>0.000</td>
<td>0.052</td>
<td>0.9582</td>
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<tr>
<td>SHORTVOL</td>
<td>0.000</td>
<td>0.000</td>
<td>0.700</td>
<td>0.4838</td>
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<tr>
<td>NBUY</td>
<td>1.701</td>
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<td>189.240</td>
<td>0</td>
</tr>
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<td></td>
<td></td>
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</tr>
<tr>
<td>Control A</td>
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</tr>
<tr>
<td>C</td>
<td>30.985</td>
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<td>0.0023</td>
</tr>
<tr>
<td>RESID(−1)^2</td>
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<td>0.001</td>
<td>4.305</td>
<td>0</td>
</tr>
<tr>
<td>GARCH(−1)</td>
<td>0.590</td>
<td>0.075</td>
<td>7.888</td>
<td>0</td>
</tr>
<tr>
<td>1/DUR</td>
<td>0.000</td>
<td>0.153</td>
<td>0.000</td>
<td>0.9996</td>
</tr>
<tr>
<td>DUR/EDUR</td>
<td>−0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>0.9999</td>
</tr>
<tr>
<td>SPREADS(−1)</td>
<td>0.000</td>
<td>0.000</td>
<td>−1.425</td>
<td>0.111</td>
</tr>
<tr>
<td>VOL</td>
<td>0.000</td>
<td>0.000</td>
<td>−3.258</td>
<td>0.0011</td>
</tr>
<tr>
<td>BIDS</td>
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<td>0.000</td>
<td>−8.943</td>
<td>0</td>
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<tr>
<td>SHORTVOL</td>
<td>0.017</td>
<td>0.089</td>
<td>0.187</td>
<td>0.852</td>
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<tr>
<td>NBUY</td>
<td>−0.001</td>
<td>0.994</td>
<td>−0.001</td>
<td>0.9991</td>
</tr>
</tbody>
</table>

GARCH(−1)) were statistically significant. This confirmed the suitability of the basic model as an appropriate specification for modelling of this data set. Changes in the number of significant coefficients from the estimated models of the three typical companies demonstrated the impact on the trading of each company across the two sample periods. An increase in the number of significant coefficients across the periods was assumed to indicate the dissemination of information related to a potential takeover before its announcement.

19 The basic model given by Eq. (6) simply incorporates the GARCH variables.

20 Estimation results for the 570 individual companies comprising the total sample are available from the authors on request.

21 The sign of the coefficient was also considered in the analysis.
coefficients across the samples for the same two microstructure variables as for the targets, changes in the percentages of the corresponding duration variables were not significant. For the control companies, the only covariate where a significant change was found in the percentages of significant model coefficients from one sample period to the next was the duration surprise. However, that change was in the other direction to that of the target and bidder groups.

4. Conclusions

Mergers and acquisitions is an area with high information asymmetry and, consequently, abnormal profit opportunities for investors. Without doubt, the effect that takeover announcements have had on the prices of target firms is a strong motive for trading with privileged information. As a consequence, movements in trading activity before a takeover announcement are expected and indicate the possible presence of informed trading and information leakage. This paper has empirically justified the use of intraday trading to capture information associated with takeover announcements, with the ACD model adopted for this purpose. Importantly, the modelling approach outlined in this study provides a means by which the timing of the inclusion of potential targets in a portfolio can be determined. This would require the creation of a trading rule, a task identified for future research.

The market behaviour of a group of companies on the Australian Stock Exchange that were subjected to a takeover offer between 2004 and 2008 was observed in order to examine how intraday activity in the targets was reflected in return volatility at least three months before the official announcement of the takeover offer. By observation of the bidders over the same period, it was concluded that the buyer side of the market was in some way affected, but to a much lesser degree. A control group of companies was also included in the analysis and the results rejected the hypothesis that the more intense trading behaviour associated with the target in the three months before the announcement was caused by publicly available industry or market related news.

Duration variables, along with spread and volume microstructure variables, were found to be important for explaining return volatility in target companies. It was also possible to observe a clear relation between trading intensity and information dissemination. The analysis supported the assumption that the intensified trading activity in the target companies closer to the event announcement was a consequence of traders who held private information. Using the approach adopted in this paper, a consistent covariate pattern for targets was established over an extensive range of companies. As a consequence, the profitable introduction of potential targets into a portfolio can be timed and the portfolio rebalanced according to information suggested by changes in company intraday trading patterns.

References


