A Model for Trade Frequency in the Presence of Announcements

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Abstract

We investigate the effect of publicly released announcements upon trade frequency using high frequency banking stocks from the Australian Stock Exchange and the Autoregressive Conditional Hazard (ACH) model of Hamilton and Jorda (2000). Unlike the ACD model, which models the timing of events, the ACH model focuses on the probability of events and facilitates the incorporation of fixed interval variables such as announcement indicators. This approach explicitly allows us to model the probability of trade in the presence of announcements. We find evidence to suggest that announcements increase the probability of trade.

Keywords: Announcements, Autoregressive Conditional Hazard Model, Poisson Model, Negative Binomial Model, Durations.

JEL Classifications: C24, C25, C41

1 Introduction

Market microstructure theories point to information as a leading influence upon market related variables such as volume, prices, spread and trading frequency. In particular, the work of Easley and O'Hara (1992) posits that the frequency of trade is indicative of the degree of information asymmetry present in the market. That is, the greater the trade frequency the greater the number of informed traders present in the market. This implies increased trade frequency surrounding announcement releases and also that trade frequency aids understanding of how information is absorbed by the market. Trade frequency is an interesting variable to investigate since the findings of French and Roll (1986) suggest that prices and volatility can change without trade, as supported empirically by Fleming and Remolona (1999).

A complement of trade frequency is the time between trades or trade duration. The irregular spacing and autoregressive nature of such data facilitated the introduction of the autoregressive conditional duration (ACD) model of Engle and Russell (1997, 1998). Numerous papers have developed the ACD framework although little research has investigated the effect of announcements upon trade durations explicitly. The work of Zhang, Russell and Tsay (2000) finds structural breaks in IBM stock transaction data that can be linked to announcements, although they do not incorporate announcement effects directly. A problem with using trade duration data as a measure of trade frequency is the presence of zero durations that exist when there are simultaneously occurring multiple trades. Zhang, Russell and Tsay (2000) use multiple-trade indicators to account for this, although, the inclusion of announcement variables within the ACD framework remains complicated by the timing of the announcements relative to the irregular spacing of the trade durations.

We apply the autoregressive conditional hazard (ACH) model of Hamilton and Jorda (2002) directly to transactions level data in order to evaluate the effect of announcements. We define a measure of trade frequency by counting the number of trades occurring within 30 second intervals for each of five banking stocks on one day of trade on the Australian Stock Exchange. This is in contrast to the original application that applied the ACH model to macroeconomic data of US Federal Funds Target Rates using one week intervals, and another application by Hamilton and Davis (2002) which investigates the probability of price changes using wholesale gasoline prices.

The ACH model consists of two components. The first models the probability of a trade occurring using a hazard model, incorporating the timing of a trade in addition to exogenous variables. Unlike logit and probit models the ACH allows the autoregressive dynamics of duration data to be incorporated succinctly. In our context, we model the probability of a trade occurring conditional on the trade durations, announcement indicators and other market related variables such as price changes, volume and spreads. The second model is a count data model that predicts the trade frequency given that a trade has occurred. Truncated-poisson models were originally developed to allow the modeling of scenarios where counts are missing either below or above a certain point, that is the data has either left or right truncation. For example, to obtain a count of the number of bus trips taken per week by an individual, it is necessary that the individual catches the bus to begin with. In this case, as in our example, the data will be truncated at zero. It is also possible to shift the data and use a standard poisson model. The application of negative binomial models allows overdispersion in the data to be incorporated.

Related work by Hall, Haustch and McCulloch (2003) uses a bivariate autoregressive conditional intensity (ACI) model of Russell (1999) to model the arrival of buy and sell orders. Maheu and McCurdy (2003) examine the conditional variance of returns implied by different news releases by using a GARCH model with an autoregressive jump intensity parameter which measures large jumps in the price process. They use a heterogeneous poisson process with a time varying conditional intensity parameter to measure the likelihood of jumps. Recent work by Gonzalez-Rivera, Lee, and Mishra (2003) also incorporates jumps in the price process, in addition to modeling the conditional probability of an alteration in cross-sectional returns when evaluating a nonlinear model of expected returns. Rydberg and Shephard (1999) use a truncated negative binomial model in their decomposition of price changes.

In this paper we find, in general, that lags of announcement indicators decrease conditional durations, leading to an increase in the probability that a trade will occur. The effect of announcements upon trade frequency is generally positive leading to an increase in trade frequency for three out of four stocks for which announcement effects are significant.

The remainder of this paper is organized as follows: Section 2 introduces the ACH model. The data is described in Section 3. Section 4 discusses the results and Section 5 offers concluding remarks and areas for future research.

2 The ACH Model

2.1 The ACH Model

The ACD model of Engle and Russell (1997,1998) can be composed in calender time so as to allow the inclusion of fixed time variables, in particular the announcement indicators. By assuming that observations occur at discrete points in time, $N(t)$ defines the cumulative number of trades that have taken place as of interval t. For example, if trade occurs in intervals 3, 4 and 6 then,

$$N(t) = \begin{cases} 0 & \text{for } t = 1, 2 \\ 1 & \text{for } t = 3 \\ 2 & \text{for } t = 4, 5 \\ 3 & \text{for } t = 6, 7, ... \end{cases} \tag{1}$$

Let $u_{N(t)}$ measure the duration associated with the last trade and initially assume that at most, each interval can contain one trade. The simplest ACD specification is the ACD(1,1) which, can be written in calender time as,

$$\psi_{N(t)} = \alpha u_{N(t)-1} + \beta \psi_{N(t)-1} \tag{2}$$

where $\psi_{N(t)} = E(u_{N(t)}|\Upsilon_{t-1})$ is the conditional mean duration and Υ_{t-1} is past information. This specification can be generalized to include more lags. Here, we initially assume that trade durations follow an exponential distribution, although we will allow for more general distributions in later research. By taking the reciprocal of the conditional trade duration, the ACD model can be used to give the probability of a trade in the next time period. This probability is also known as the hazard rate. For example, if the conditional mean time between trade was 10 seconds, then the probability of a trade occurring in the next second will be 1/10, i.e. there will be a 10% chance of trade occurring in the next second. The hazard rate or probability of a trade conditional on past information $h_t = \Pr[N(t) \neq N(t-1)|\Upsilon_{t-1}]$ is given by,

$$h_t = 1/\psi_{N(t-1)}. \tag{3}$$

The hazard rate can be expanded to incorporate a constant and exogenous variables contained in the vector $\mathbf{z}_{t-1}$ via the relationship

$$h_t = 1/(\psi_{N(t-1)} + \boldsymbol{\delta}'\mathbf{z}_{t-1}). \tag{4}$$

To ensure that the hazard probabilities lie within the (0,1) interval, the denominator of (4) is replaced with the larger of $[\psi_{N(t-1)} + \boldsymbol{\delta}'\mathbf{z}_{t-1}]$ and 1.0001, and a sigmoidal function is used to ensure differentiability between the values of 1.0001 and 1.1, as explained in Hamilton and Jorda (2002).

Define x_t to be equal to one for when a trade occurs and zero otherwise. The probability of a trade occurring given past information is given by

$$g(x_t|\Upsilon_{t-1};\theta_1) = h_t^{x_t}(1-h_t)^{1-x_t}, \tag{5}$$

where $\theta_1 = (\boldsymbol{\delta}', \alpha', \beta')$ so that the log likelihood function is,

$$L_1(\theta_1) = \sum_{t=1}^{T}[x_t \log(h_t) + (1-x_t)\log(1-h_t)] \tag{6}$$

The log likelihood is maximized with respect to θ_1. To ensure stationarity of the conditional durations, restricting α, $\beta \geq 0$, and $0 \leq \alpha + \beta \leq 1$ may be required.

2.2 Count Data Models

The second stage of the ACH model predicts the number of trades that occur in each interval where $x_t \neq 0$. Let Y be the random variable that indicates the number of trades that occur at each interval for which $x_t \neq 0$, thus, Y can take on the values of $y_t = 1, 2, 3, ...$One possible model for such data might be a poisson count data model, truncated at zero. For such a distribution the probability that the number of trades equals a value y_t given that $Y > 0$, where $y_t = 1, 2, 3, 4, ...$ is given by

$$\Pr(Y = y_t \,|\, y_t > 0) = q(y_t|\Upsilon_{t-1}) = \frac{\exp(-\lambda_t)\lambda_t^{y_t}}{(1-\exp(-\lambda_t))y_t!}, \qquad y_t = 1, 2, 3, ... \tag{7}$$

where $\lambda_t = E(y_t)$ is the mean parameter of the untruncated distribution. Since the mean parameter λ_t might change according to the prevailing market conditions, it is natural to set $\lambda_t = \exp(w_t'\gamma)$, where w_t' is a vector of explanatory variables such as the announcement indicators, spread, price changes and volume and γ is a vector of parameters.

The log likelihood function can be written as,

$$L_{2'}(\theta_2) = \sum_{t=1}^{T}[-\lambda_t + y_t \log(\lambda_t) - \log(y_t!) - \log(1-\exp(-\lambda_t))] \tag{8}$$

where $\theta_2 = (\gamma')$.

The truncation-at-zero of the trade data shifts the mean upwards. An alternative method of modeling the trade data would involve shifting the trade count data by subtracting one and then applying a standard poisson model. The trade count data is now viewed as *excess* trades and the resulting distribution is known as a "shifted-poisson", which is characterized by underdispersion i.e. the variance is smaller than the mean.

Count data often does not satisfy the underlying assumptions of the poisson distribution, especially the equidispersion assumption that the mean and variance of the poisson distribution are equal. Typically count data features overdispersion so that the variance is much larger than the mean. If the poisson distribution is utilized in the presence of overdispersion, then the resulting standard errors are under estimated. A more flexible distribution such as the negative binomial, allows overdispersion or heterogeneity in the variance so that the variance is larger than the mean. The negative binomial distribution generalizes the variance such that:

$$Var(y_t) = \lambda_t + \phi\lambda_t^p, \tag{9}$$

where ϕ is a scalar overdispersion parameter, and p is a constant indicating the type of overdispersion. If $p = 1$ then $Var(y_t) = \lambda_t(1+\phi)$ and the overdispersion is linear in the mean yielding the Negative Binomial I distribution. If $p = 2$, then the $Var(y_t) = \lambda_t(1+\phi\lambda_t)$ yielding the Negative Binomial II distribution. The Negative Binomial II distribution is given by,

$$\Pr(Y = y_t\,) = q(y_t|\Upsilon_{t-1}) = \frac{\Gamma(\phi^{-1}+y_t)}{\Gamma(\phi^{-1})(y_t)!}\left(\frac{\phi^{-1}}{\phi^{-1}+\lambda_t}\right)^{\phi^{-1}}\left(\frac{\lambda_t}{\phi^{-1}+\lambda_t}\right)^{y_t}, \qquad y_t = 0, 1, 2, 3, ... \tag{10}$$

where $\Gamma(.)$ is the gamma function. The extent of the overdispersion can be measured by taking the ratio of $Var(y_t)$ to the mean $E(y_t)$,

$$\frac{Var(y_t)}{E(y_t)} = 1 + \phi\lambda_t. \tag{11}$$

Evaluation of the null $H_0 : \phi = 0$ using either a likelihood ratio test or Wald test indicates the significance of the estimated overdispersion parameter. Note that as $\phi \to 0$, the negative binomial distribution collapses to the poisson distribution. We focus on the Negative Binomial II distribution, which can be treated in a similar manner to the Poisson distribution in that the trade count data can either be modified and a "shifted-negative-binomial" used, or the Negative Binomial II distribution can be truncated to allow non-zero counts.

2.3 The Combined Model

The combination of the ACH and the count data model yields the joint probability of observing x_t and y_t conditional on past information, which can be written as the product of the marginal and conditional distributions as,

$$f(x_t, y_t|\Upsilon_{t-1}; \theta_1, \theta_2) = g(x_t|\Upsilon_{t-1}; \theta_1).q(y_t|x_t, \Upsilon_{t-1}; \theta_2) \tag{12}$$

with log likelihood,

$$\sum_{t=1}^{T} \log f(x_t, y_t|\Upsilon_{t-1}; \theta_1, \theta_2) = L_1(\theta_1) + L_2(\theta_2) \tag{13}$$

where $L_1(\theta_1) = \sum_{t=1}^{T} \log(x_t|\Upsilon_{t-1}; \theta_1)$ and $L_2(\theta_2) = \sum_{t=1}^{T} x_t, \log q(y_t|x_t, \Upsilon_{t-1}; \theta_2)$. Note that for $L_2(\theta_2)$ we are conditioning on $x_t = 1$, so that only positive integer values greater than zero for y_t are considered.

It is possible to maximize (13) by maximizing $L_1(\theta_1)$ and $L_2(\theta_2)$ separately to obtain efficient and consistent parameter estimates, provided that θ_1 and θ_2 do not share common parameters. However, if θ_1 and θ_2 do share common parameters, then parameter estimates remain consistent but are no longer efficient.

3 Data

The data consists of one day of trade from five banking stocks on the Australian Stock Exchange in the month of November 2001. Only one day of trade for each of the stocks was examined, in order to keep the analysis tractable and manageable. Separate days for each of the banks were chosen for analysis, based on the number and type of announcements occurring on each of those days. The banks are the ANZ Bank (ANZ), Commonwealth Bank (CBA), National Australia Bank (NAB), St George Bank (SGB) and the Westpac Bank (WBC). The chosen days are 19th for ANZ, 5th for CBA, 8th for NAB, 7th for SGB and the 2nd for WBC. The types of announcements are listed in Appendix 1.

The first twenty minutes of the trading day were removed to eliminate overnight trading effects. The transactions data for each stock was aggregated into 30 second intervals, beginning at 10.20am and ending at 4.00pm. Within each of the 30 second intervals the number of trades were counted.

Bid and ask prices were determined by using the best bid and the best ask price from among the trades occurring within each interval. For intervals with no trade, the bid and ask prices were taken from the previous interval within which trades had occurred. Volume for intervals for which trades occurred was determined by aggregating the trade sizes of the individual trades within that interval. Prices were calculated as the average of the best bid and ask prices in dollars.

From each of the datasets a number of other variables were then created, including the natural log of both the percentage spread and percentage spread changes in percentage points denoted by **Ln(S)** and **Ln(SΔ)** respectively. **Price** Δ is the price change calculated as the difference in prices between intervals t and t-1 in cents. Prior to taking the natural log, the volume variable was scaled by dividing through by 1000. The announcement indicator, **ANN** was defined as one for those intervals in which an announcement occurred and zero otherwise. A trade indicator variable was similarly defined as one for intervals in which trades occurred and zero otherwise. Ten lags of each of the above variables, corresponding to 5 minutes of calender time were also created.

Typically trade duration data displays a distinct inverted-U shape across the trading day, with shorter durations occurring at the beginning and end of the trading day and longer durations corresponding to the lunch period. This diurnal pattern can be removed by using smoothing splines and assuming that the inverted-U shape pattern has a multiplicative relationship with the durations such that, $\widetilde{\tau}_i = \tau_i/\xi(t_{i-1})$, where τ_i are the durations, $\widetilde{\tau}_i$ are the adjusted durations and $\xi(t_{i-1})$ is the smoothing spline. The diurnal pattern has not been removed from the data used in this paper since it requires estimation across the many trading days in order to obtain the effect of the average diurnal trading pattern. Instead, to model the diurnal pattern, a proxy variable for the time of day effects - the previous-trade variable, was used. **Prev. Trade** counts the number of intervals occurring since the previous non-zero trade interval, and its minimum value will be one, occurring when trade occurs in consecutive intervals. The previous trade variable will be low early and late in the day when trade is frequent, and high in the middle of the day when trading is sparse. It works by shifting the constant term within the ACH model to allow the conditional durations to be larger for when the time between non-zero trade intervals is large.

Another important issue is that of the interval length, which has been set equal to 30 seconds for this paper. This may be too small or too large, depending on the trade frequency of the individual stocks. If the interval is too small relative to the trade frequency then there will be numerous intervals in which zero trade and market activity occurs causing the data to be zero inflated. The reverse case will lead to an over-aggregation of the data causing a loss of information. Ultimately, the intervals will be tailored to the trade frequency of each of the stocks.

When trade halt data becomes available, a new variable will be developed to explicitly incorporate the effect of market imposed halts upon trade frequency.

4 Empirical Results and Discussion

4.1 Results for the ACH model

The trade durations for each of the stocks displays significant autocorrelation for up to 15 lags, as presented in Table 1 below,

TABLE 1 Q statistics for the Trade Durations

	ANZ	**CBA**	**NAB**	**SGB**	**WBC**
$\mathbf{Q}_{(15)}$	4009.60	842.26	936.66	293.95	1918.70

The critical value for the 5% level of significance is $\chi^2_{(15)} = 24.996$.

The autocorrelation in the trade durations is modeled by $\psi_{N(t)-1}$ within equation (3). $\psi_{N(t)-1}$ could be generalized to allow different lag structures and different distributions such as the generalized gamma, but in this paper we employ an exponential ACH(1,1) form.

For each of the banks several models for the ACH component were estimated, and since each of the banks display different dynamics a representative model for each of the stocks has been presented separately within Table 2. In each of the models, the sum of the estimated coefficients for beta and alpha remain less than one ensuring that the conditional durations are stationary.

Across each of the stocks the most consistent effect comes from the announcement indicator variables which are always significantly negative, confirming the theory of Easley and O'Hara (1992), who suggest that the greater the time between trade, the less likely it is that new information exists. The announcement indicators directly measure the release of new information, so that we would expect the estimated coefficients to be negative causing the conditional durations to decrease. Our results support this theory, and suggest that announcements increase the probability of trade.

The effect of the log volume is also predominantly negative across each of the stocks, consistent with Easley and O'Hara's (1987) prediction that large trades are more likely to come from informed traders. If informed traders maximize profit by trading large amounts as often as possible, then the time between trades will decrease in the presence of informed traders and large volume.

Price changes can be viewed as a measure of volatility. Engle (2000) finds a negative relationship between price volatility per second and the time between trades, whereas we find that the sign of the price change variable differs across each of the stocks. It may be the case that the price effects should be modeled by using the absolute value of price changes as a measure of volatility. Also, one might adopt the approach of Fletcher (1995) who defines an indicator variable i.e. $I_{Pt} = 1$ for when the price change variable is negative and zero otherwise, and then use the signed absolute value of the price change variable, i.e. $I_{Pt}.|Ln(\Pr ice\Delta\ )_{t-1}|$, as an indicator of bad news. By separating these two effects, the effect of price changes may become more distinct.

The effect of the spread upon durations is not immediately obvious and few theoretical papers discuss the direct impact of the spread on trade durations. The work of Demsetz (1968) and Glosten and Milgrom (1985) imply that there is a positive relationship between the spread and trade durations, since the spread can be interpreted as a transaction cost so that the larger the transaction cost, the longer the durations[1]. We would thus expect a positive relationship between the spread and trade durations. However, according to the model of Easley and O'Hara (1992), the probability that new information exists is reduced as the time between trades increases, so that the spread should become more narrow reflecting the decreased informational trade. This suggests a negative relationship between trade durations and the spread. We find differing signs on the spread variable across each of the stocks, in line with opposing theories on the effect of the spread upon trade durations.

Turning to individual stocks, we find that the estimated coefficients on the announcement indicators for ANZ are generally significantly negative. In particular, if an announcement occurred two lags (i.e. one minute in calender time) prior to the current time period, then trade durations are reduced, causing an increase in the probability of trade. The previous trade variable is also significantly positive. The estimated coefficient on volume is significantly negative suggesting that as volume increases then the conditional durations will decrease causing an increase in the probability of a trade.

The significant coefficients in the estimated ACH model for ANZ fall into two groups: those at low lags of one or two lagged periods, and coefficients at high lags of seven and ten lagged periods. Although the exact lags differ, this is also true for CBA, SGB and WBC, with the sole exception of NAB. It is often the price change and spread variables that are significant at these high lags suggesting that the probability of trade in the current period is affected by information contained from up to five minutes prior to the current period. One explanation of this behavior may be due to small rallies and falls in the share price prompting traders to act upon the combination of more recent information, as contained in the lower lags, and past information as contained in the higher lags. For example, if the share price is rallying then traders may only wish to enter the market and buy shares when the price appears to be continually increasing. A second explanation of this behavior may be due to the secondary round of trade compensating for over-reactions that often occur after information is received in the market, as suggested by Ederington and Lee (1995) and Fleming and Remolona (1999). A more direct measure for over-reaction may be better incorporated by including interactions between each of the explanatory variables and the announcement indicators.

CBA announcements increase the probability of trade, but unlike the results for ANZ, the price change estimated coefficients for CBA are significantly negative, suggesting that if price changes are positive then conditional durations are decreased and the probability of a trade is increased. When the lagged log percentage spread variables are significant they are positive, such that the larger the percentage spread the greater the conditional duration and the less likely it is that trade will occur.

For NAB the estimated coefficients on the announcement indicator, log volume and log percentage spread when significant are negative, leading to a reduction in the conditional durations and an increase in the probability of a trade. Only the lower lags of volume and spread are significant,

[1] See Ulph (1999) for more details

indicating that only short run dynamics are important for predicting the probability of trade.

The previous trade variable is positive for SGB, indicating significant daily effects, and announcements increase the probability of trade for almost five minutes. The estimated coefficients for lag one of the log volume variable is positive, so that if a large volume of stock was traded 30 seconds prior to the current time period, then conditional durations are increased and the probability of trade is reduced. The log percentage spread variables, when significant have a negative effect on trade durations, while the price change variable has a positive effect.

For WBC, the probability of trade increases about 4.5 minutes after an announcement. Other than the previous trade variable, which suggests significant daily trading patterns in WBC stocks, the only other variables that affect trading frequency are the spread and spread changes, which both increase trade durations and decrease the probability of trade.

TABLE 2 Estimates of the ACH Component (Equation (4))

ANZ -19th Nov. 2001		**CBA-5th Nov. 2001**		**NAB-7th Nov. 2001**	
Beta	0.823**	**Beta**	0.94**	**Beta**	0.894**
	(0.061)		(0.019)		(0.035)
Alpha	0.075**	**Alpha**	0.054**	**Alpha**	0.080**
	(0.030)		(0.016)		(0.026)
Constant	-0.188	**Constant**	-0.920**	**Constant**	-0.634**
	(0.215)		(0.250)		(0.134)
Prev. Trade	0.120**	**Ann**$_{t-2}$	2.209	**Ann**$_{t-2}$	-0.299*
	(0.072)		(2.281)		(0.129)
Ann$_{t-2}$	-0.715**	**Ann**$_{t-7}$	-0.585**	**Ln(S)**$_{t-3}$	-0.064*
	(0.120)		(0.195)		(0.026)
Ann$_{t-7}$	-0.630	**Ln(vol)**$_{t-7}$	-0.091**		
	(1.252)		(0.033)		
Ann$_{t-10}$	0.210*	**Price** Δ_{t-7}	-0.059*		
	(0.843)		(0.024)		
Ln(Vol)$_{t-1}$	-0.073*	**Ln(S)**$_{t-5}$	0.203**		
	(0.033)		(0.063)		
Price Δ_{t-2}	0.095*				
	(0.037)				
PriceΔ_{t-10}	0.210*				
	(0.084)				
Ln(SΔ**)**$_{t-10}$	-0.012*				
	(0.005)				
LogL	-409.324	**LogL**	-406.101	**LogL**	-372.607
$\overline{\psi}$	0.940	$\overline{\psi}$	1.522	$\overline{\psi}$	1.113
$\overline{\tau}$	2.447	$\overline{\tau}$	1.713	$\overline{\tau}$	1.499

Table 2 presents estimated coefficients for the ACH component. ** indicates significance at the 1% level, * indicates significance at the 5% level. $\overline{\psi}$ and $\overline{\tau}$ are the average conditional durations and unconditional durations respectively.

SGB-8th Nov. 2001		WBC-2nd Nov. 2001	
Beta	0.927**	**Beta**	0.908**
	(0.033)		(0.035)
Alpha	0.028	**Alpha**	0.053*
	(0.015)		(0.022)
Constant	0.142	**Constant**	-0.770**
	(0.528)		(0.215)
Prev. Trade	0.324**	**Prev. Trade**	0.197*
	(0.086)		(0.079)
Ann$_{t-1}$	-1.574**	**Ann**$_{t-9}$	-1.242**
	(0.201)		(0.350)
Ann$_{t-2}$	-1.235**	**Ln(S)**$_{t-3}$	0.348*
	(0.424)		(0.143)
Ann$_{t-5}$	-0.699**	**Ln(S Δ)**$_{t-8}$	0.358**
	(0.226)		(0.116)
Ann$_{t-6}$	-0.485		
	(0.421)		
Ann$_{t-8}$	-0.532		
	(0.644)		
Ann$_{t-9}$	-1.472**		
	(0.261)		
Ln(Vol)$_{t-1}$	0.266*		
	(0.124)		
Ln(Vol)$_{t-2}$	-0.143		
	(0.157)		
Price Δ_{t-4}	0.333**		
	(0.099)		
Ln(S)$_{t-2}$	-0.152*		
	(0.075)		
LogL	-408.639	**LogL**	-417.660
$\overline{\psi}$	1.160	$\overline{\psi}$	1.133
$\overline{\tau}$	2.645	$\overline{\tau}$	2.103

4.2 Results for the Poisson and Negative Binomial Models

Prior to modeling the trade count data, the mean and the variance were calculated as presented in Table 3,

TABLE 3 Mean and Variance of the Trade Count Data

Stock	ANZ	CBA	NAB	SGB	WBC
Mean	2.766	2.718	3.469	1.866	2.548
Variance	5.948	6.050	8.680	2.074	4.347

Note that the trade count data does not contain zero counts. However, when the mean of the shifted trade count data is calculated to include zero counts, the mean decreases by one.

From Table 3 it can be seen that for all the banks, the variance is larger than the mean violating the equidispersion assumption of the poisson distribution. It is therefore likely that estimated standard errors for the shifted-poisson models are under-estimated due to the use of the incorrect distribution. Rather than shifting the data, another way to model the trade counts is to shift the mean using the truncated-poisson model. The results shown in Table 4 for the shifted-poisson and truncated-poisson models, indicate that the effect of the natural log of volume and the announcement indicators are generally positive for all stocks, increasing the number of trades, whilst the effect of the price changes and natural log of the percentage spread tend to differ in sign.

The main problem in using the poisson is that it does not allow overdispersion to be modeled. If overdispersion is ignored, then the results from using the poisson distribution will still be consistent but will now be inefficient. To measure overdispersion, the shifted-negative binomial and truncated-negative binomial models were estimated. For both these models using a Wald test[2], the estimated overdispersion parameter $\widehat{\phi}$ is highly significant and many of the variables from the shifted-poisson and truncated-poisson models are no longer significant, suggesting that the standard errors in both the shifted-poisson and truncated-poisson models were underestimated. Furthermore, Cameron and Trivedi (1998) explain that when using the Negative Binomial II model with $\widehat{\phi}$ values around 0.5 and low counts of 0,1 and 2, the model has mild overdispersion, and with high counts of 10 or more the model has severe overdispersion. All of the stocks have high counts and each of the estimated overdispersion parameters are large indicating a large degree of overdispersion in the data.

After accounting for overdispersion the announcement variables are no longer significant (except in the WBC case). Thus, although announcements increase the probability of trade in a given interval (via the ACH component), they do not increase the number of trades in intervals when trading takes place. Past volume generally increases the number of trades. The most effective variables within the negative-binomial and truncated-negative binomial models are the natural log of the scaled volume, price changes and the natural log of the percentage spread changes. When the log volume variable is significant, it has a positive impact. For both the price change and log

[2] When $\phi = 0$, the Negative Binomial model collapses to the Poisson model. Using a Wald test for overdispersion such that $\phi > 0$, the significance of ϕ can be evaluated even though the restriction means ϕ cannot be less than zero. Hence, the distribution of the Wald statistic is nonstandard, see Cameron and Trivedi (1998) for more details.

percentage spread change variables, the coefficients differ in sign across stocks. This highlights the potentially asymmetric effects of these variables, which like the ACH component may be better modeled using the approach taken by Fletcher (1995) as mentioned earlier.

Interestingly, the results for SGB suggest that the only significant estimated parameter is that of the overdispersion parameter, $\widehat{\phi}$, which is disproportionately high in comparison to the values of $\widehat{\phi}$ for the other stocks. It is thus possible that the Negative Binomial II distribution with a quadratic variance function is inappropriate, and instead some other form or even distribution for the trade counts will be more appropriate. Note that of the five stocks, SGB is the least liquid, with much thinner trading and fewer transactions in comparison to the remaining four stocks, it is possible that the interval of 30 seconds is too small for SGB and a larger interval of up to two minutes may be more appropriate.

TABLE 4

Panel A: Count data models for ANZ

Shifted-Poisson		**Trunc. Poisson**		**Shifted-Negbin**		**Trunc. NegBin**	
Constant	0.375**	**Constant**	0.700**	**Constant**	0.548**	**Constant**	0.606**
	(0.059)		(0.079)		(0.063)		(0.010)
$\mathbf{Ann}_{t-5}$	0.847*	$\mathbf{Ann}_{t-5}$	0.581	**Price** Δ_{t-1}	-0.153*	**Price** Δ_{t-1}	-0.150*
	(0.337)		(0.314)		(0.007)		(0.072)
$\mathbf{Ln(Vol)}_{t-2}$	0.089**	$\mathbf{Ann}_{t-6}$	0.731*	**Psi**	0.861**	**Psi**	0.831**
	(0.029)		(0.351)		(0.104)		(0.184)
Price Δ_{t-1}	-0.164**	$\mathbf{Ln(Vol)}_{t-2}$	0.075**				
	(0.046)		(0.026)				
Price Δ_{t-3}	-0.143**	**Price** Δ_{t-1}	-0.121**				
	(0.046)		(0.043)				
Price Δ_{t-4}	-0.163**	**Price** Δ_{t-3}	-0.112**				
	(0.048)		(0.044)				
		Price Δ_{t-4}	-0.149**				
			(0.047)				
		$\mathbf{Ln(S)}_{t-6}$	0.073				
			(0.077)				
		$\mathbf{Ln(S\Delta)}_{t-3}$	-0.018*				
			(0.007)				
		$\mathbf{Ln(S\Delta)}_{t-4}$	-0.002*				
			(0.008)				
		$\mathbf{Ln(S\Delta)}_{t-5}$	-0.017				
			(0.009)				
LogL	-761.844	**LogL**	-712.484	**LogL**	-668.997	**LogL**	-669.381
% Correct		**% Correct**		**% Correct**		**% Correct**	

Table 4 presents estimated coefficients for the Count Data component. ** indicates significance at the 1% level, * indicates significance at the 5% level.

Panel B: Count data models for CBA

Shifted-Poisson		**Trunc. Poisson**		**Shifted-Negbin**		**Trunc. NegBin**	
Constant	0.088	**Constant**	0.429**	**Constant**	0.0091	**Constant**	0.098
	(0.085)		(0.072)		(0.102)		(0.152)
Ln(Vol)$_{t-1}$	0.172**	**Ln(Vol)**$_{t-1}$	0.108**	**Ln(Vol)**$_{t-1}$	0.152*	**Ln(Vol)**$_{t-1}$	0.152*
	(0.039)		(0.033)		(0.069)		(0.072)
Ln(Vol)$_{t-6}$	0.125**	**Ln(Vol)**$_{t-6}$	0.097**	**Ln(Vol)**$_{t-6}$	0.147*	**Ln(Vol)**$_{t-6}$	0.147*
	(0.037)		(0.034)		(0.069)		(0.071)
Ln(Vol)$_{t-8}$	0.160**	**Ln(Vol)**$_{t-9}$	0.106**	**Ln(Vol)**$_{t-8}$	0.166*	**Ln(Vol)**$_{t-8}$	0.165*
	(0.038)		(0.034)		(0.080)		(0.082)
Price Δ_{t-1}	0.071*	**Price** Δ_{t-1}	0.071**	**Price** Δ_{t-4}	0.111*	**Price** Δ_{t-4}	0.110*
	(0.029)		(0.025)		(0.046)		(0.047)
Price Δ_{t-2}	0.073**	**Price** Δ_{t-2}	0.055**	**Ln(SΔ)**$_{t-10}$	0.182*	**Ln(SΔ)**$_{t-10}$	0.181*
	(0.028)		(0.024)		(0.072)		(0.073)
Price Δ_{t-4}	0.134**	**Price** Δ_{t-4}	0.115**	**Psi**	0.959**	**Psi**	0.979**
	(0.030)		(0.027)		(0.122)		(0.252)
Price Δ_{t-5}	0.065*	**Ln(S)**$_{t-10}$	0.223**				
	(0.029)		(0.054)				
Ln(S)$_{t-1}$	-0.263**	**Ln(SΔ)**$_{t-7}$	0.181**				
	(0.065)		(0.057)				
Ln(S)$_{t-10}$	0.210**						
	(0.071)						
Ln(SΔ)$_{t-7}$	0.255**						
	(0.064)						
Ln(SΔ)$_{t-10}$	0.160*						
	(0.075)						
LogL	-865.995	**LogL**	-833.062	**LogL**	-758.001	**LogL**	-758.052

Panel C: Count data models for NAB

Shifted-Poisson		**Trunc. Poisson**		**Shifted-Negbin**		**Trunc. NegBin**	
Constant	0.276**	**Constant**	0.694**	**Constant**	0.368**	**Constant**	0.435**
	(0.072)		(0.066)		(0.105)		(0.126)
$\mathbf{Ann}_{t-5}$	-0.713**	$\mathbf{Ann}_{t-5}$	-0.581**	$\mathbf{Ln(Vol)}_{t-1}$	0.125**	$\mathbf{Ln(Vol)}_{t-1}$	0.122**
	(0.238)		(0.216)		(0.048)		(0.047)
$\mathbf{Ann}_{t-7}$	-0.892**	$\mathbf{Ann}_{t-7}$	0.710*	$\mathbf{Ln(Vol)}_{t-5}$	0.109*	$\mathbf{Ln(Vol)}_{t-5}$	0.107*
	(0.233)		(0.279)		(0.045)		(0.044)
$\mathbf{Ann}_{t-8}$	-0.548	$\mathbf{Ann}_{t-8}$	-0.465*	$\mathbf{Ln(Vol)}_{t-7}$	0.111*	$\mathbf{Ln(Vol)}_{t-7}$	0.109**
	(0.233)		(0.212)		(0.042)		(0.042)
$\mathbf{Ln(Vol)}_{t-1}$	0.106*	$\mathbf{Ln(Vol)}_{t-1}$	0.087**	$\mathbf{Ln(S\ \Delta)}_{t-9}$	-0.147*	$\mathbf{Ln(S\ \Delta)}_{t-9}$	-0.144**
	(0.026)		(0.023)		(0.072)		(0.070)
$\mathbf{Ln(Vol)}_{t-5}$	0.098**	$\mathbf{Ln(Vol)}_{t-5}$	0.082**	**Psi**	0.901**	**Psi**	0.818*
	(0.026)		(0.023)		(0.095)		(0.155)
$\mathbf{Ln(Vol)}_{t-7}$	0.092**	$\mathbf{Ln(Vol)}_{t-7}$	0.076**				
	(0.026)		(0.023)				
$\mathbf{Price\Delta}_{t-2}$	0.049**	$\mathbf{Price\Delta}_{t-2}$	0.037*				
	(0.017)		(0.016)				
$\mathbf{Ln(S)}_{t-6}$	0.133**	$\mathbf{Ln(S)}_{t-2}$	0.089*				
	(0.043)		(0.040)				
$\mathbf{Ln(S)}_{t-10}$	0.124*	$\mathbf{Ln(S)}_{t-6}$	0.118**				
	(0.049)		(0.039)				
$\mathbf{Ln(S\Delta)}_{t-9}$	-0.115*	$\mathbf{Ln(S\Delta)}_{t-9}$	-0.164**				
	(0.054)		(0.041)				
LogL	-1217.300	**LogL**	-1146.735	**LogL**	-1032.610	**LogL**	-1032.583

Panel D: Count data models for SGB

Shifted-Poisson		**Trunc. Poisson**		**Shifted-Negbin**		**Trunc. NegBin**	
Constant	-0.276*	**Constant**	0.609**	**Constant**	-0.144	**Constant**	-1.143
	(0.116)		(0.048)		(0.108)		(1.083)
Ann$_{t-3}$	1.070**	**Ann**$_{t-3}$	0.723*	**Psi**	1.619**	**Psi**	5.247
	(0.356)		(0.296)		(0.333)		(7.227)
Ln(Vol)$_{t-3}$	0.176**	**Price** Δ_{t-2}	0.141*				
	(0.067)		(0.062)				
Price Δ_{t-2}	0.287**	**Ln(S**Δ**)**$_{t-1}$	0.156*				
	(0.087)		(0.067)				
Ln(S)$_{t-6}$	-0.012	**Ln(S**Δ**)**$_{t-6}$	-0.150*				
	(0.086)		(0.071)				
Ln(SΔ**)**$_{t-1}$	0.329**						
	(0.085)						
LogL	-332.231	**LogL**	-373.607	**LogL**	-305.667	**LogL**	-305.817

Panel E: Count data models for WBC

Shifted-Poisson		Trunc. Poisson		Shifted-Negbin		Trunc. NegBin	
Constant	0.253**	**Constant**	0.639**	**Constant**	0.164	**Constant**	0.296
	(0.088)		(0.079)		(0.140)		(0.158)
Ann$_{t-1}$	0.591**	**Ann**$_{t-1}$	0.556**	**Ann**$_{t-1}$	0.789*	**Ann**$_{t-1}$	0.754*
	(0.181)		(0.163)		(0.388)		(0.367)
Ann$_{t-4}$	0.483*	**Ln(Vol)**$_{t-3}$	0.098**	**Ln(Vol)**$_{t-3}$	0.128**	**Ln(Vol)**$_{t-3}$	0.123**
	(0.199)		(0.028)		(0.049)		(0.047)
Ann$_{t-8}$	-0.832*	**Ln(Vol)**$_{t-10}$	0.095**	**Ln(Vol)**$_{t-10}$	0.127**	**Ln(Vol)**$_{t-10}$	0.121**
	(0.412)		(0.027)		(0.047)		(0.045)
Ln(Vol)$_{t-3}$	0.101**	**Price** Δ_{t-4}	0.312**	**Price** Δ_{t-4}	0.387**	**Price** Δ_{t-4}	0.372**
	(0.032)		(0.071)		(0.121)		(0.115)
Ln(Vol)$_{t-10}$	0.108**	**Ln(S)**$_{t-1}$	-0.249**	**Ln(S)**$_{t-1}$	-0.282	**Ln(S)**$_{t-1}$	-0.273
	(0.030)		(0.089)		(0.157)		(0.151)
Price Δ_{t-4}	0.331**	**Ln(SΔ)**$_{t-4}$	-0.299**	**Ln(SΔ)**$_{t-4}$	-0.385*	**Ln(SΔ)**$_{t-4}$	-0.371*
	(0.080)		(0.090)		(0.165		(0.106)
Price Δ_{t-6}	-0.217*	**Ln(SΔ)**$_{t-10}$	-0.190*	**Ln(SΔ)**$_{t-10}$	-0.224*	**Ln(SΔ)**$_{t-10}$	-0.217*
	(0.076)		(0.085)		(0.111)		(0.106)
Ln(S)$_{t-1}$	-0.329*			**Psi**	0.810**	**Psi**	0.671**
	(0.098)				(0.138)		(0.217)
Ln(SΔ)$_{t-4}$	-0.369*						
	(0.100)						
Ln(SΔ)$_{t-10}$	-0.226**						
	(0.093)						
LogL	701.385	**LogL**	-680.247	**LogL**	-636.631	**LogL**	-636.693

5 Conclusions, Limitations and Future Work

In this paper we use the ACH model of Hamilton and Jorda (2002) to study the impact of firm specific announcements upon trade frequency. The ACH model consists of two components: the first models the probability of a trade, and the second models the trade frequency. The first component, the ACH, uses an autoregressive conditional duration specification to model the autocorrelation in the time between non-zero trade intervals. The ACH also incorporates exogenous variables such as the announcement indicators, spread, price and percentage spread changes, and volume. We find that the effect of the announcement indicators are negative across all of the stocks leading to a decrease in the conditional durations which in turn leads to an increase in the probability of a trade.

The ACH component in this paper assumed an exponential distribution for the trade durations, however, this could be generalized using alternate distributions such as the generalized gamma and log-normal. It is also possible to use higher order lag structures other than the ACH(1,1). This has been left for future work.

The second component uses poisson and negative binomial specifications to model the non-zero trade counts. The trade count data consists of non-zero counts, negating the direct application of the poisson distribution. In this scenario, truncated models can be used. Alternatively, the data can be "shifted" by subtracting one from each count to ensure the existence of zero counts so that the poisson and negative binomial models are valid. The negative binomial models were estimated to check whether the variance of the trade count data was overdispersed relative to the mean. All stocks exhibited overdispersion and interestingly, the majority of significant variables from the shifted-poisson and truncated-poisson models tend to lose significance when overdispersion is accounted for. We find that announcement indicators no longer affect the number of trades even though in the ACH component, announcements have a strong impact on the probability of a trade. Within the negative binomial models, price changes and volume are the best predictors for the trade count data.

The modeling of the trade count data can be refined using Katz, Double Poisson and Generalized poisson models, which allow for underdispersion which may be more appropriate for days without announcements. It is also possible to use a hurdle model for the "shifted" data. The hurdle model consists of two parts, the first a binary outcome indicating the probability of a non-zero outcome, whilst the second model is a truncated count data model. In our case it is possible that shifting the data causes the quantity of zeros to be larger than a poisson distribution will allow which, in addition to the extreme counts, causes another form of overdispersion. The additional zeros may also be modeled using a zero inflated poisson (ZIP) model. Future work will investigate these specifications.

Finally, it is important to note that the Australian Stock Exchange will sometimes halt trade if it believes that an announcement is price sensitive. None of the announcements included in this paper were price sensitive and no trading halts occurred. We aim to include price sensitive announcements and trading halt information when it becomes available in a wider framework of the effects of announcements upon trading frequency.

6 Appendix 1

Time	ANZ Announcements 19th November 2001
11:25:06	Open Briefing:SecureNet MD on ANZ Alliance
11:43:50	Open Briefing:SecureNet MD on ANZ Alliance
14:27:18	ANZ Directors Declare Dividend
15:52:50	ANZ Directors Declare Dividend
	CBA Announcements 5th November 2001
13:23:32	Appendix 3B - Exercise of Executive Options
13:26:54	Appendix 3B - Employee Share Acquisition
13:29:59	Appendix 3B - Equity Reward Plan
13:35:07	Appendix 3B - Equity Reward Plan
15:20:03	GLD - Change in Substantial Holding from CBA
15:23:19	GDG - Change in Substantial Holding from CBA
15:23:50	ION - Change in Substantial Holding from CBA
	NAB Announcements - 8th November 2001
11:17:56	Supplementary Offering Circular NABWGF
11:44:44	2001 Profit Announcement - Full Year Result 3/19
11:47:02	2001 Profit Announcement - Full Year Result 2/19
11:48:35	Preliminary Final Report 4/4
11:57:52	2001 Profit Announcement - Full Year Result 1/19
12:06:17	2001 Profit Announcement - Full Year Result 4/19
12:37:54	2001 Profit Announcement - Full Year Result 5/19
12:53:18	2001 Profit Announcement - Full Year Result 6/19
13:22:12	2001 Profit Announcement - Full Year Result 7/19
13:35:53	2001 Profit Announcement - Full Year Result 8/19
14:03:09	2001 Profit Announcement - Full Year Result 10/19
14:04:22	2001 Profit Announcement - Full Year Result 12/19
14:17:38	2001 Profit Announcement - Full Year Result 9/19
14:32:54	2001 Profit Announcement - Full Year Result 16/19
14:47:15	2001 Profit Announcement - Full Year Result 18/19
14:48:03	2001 Profit Announcement - Full Year Result 17/19
14:51:07	2001 Profit Announcement - Full Year Result 14/19
15:13:23	2001 Profit Announcement - Full Year Result 11/19
15:33:39	Preliminary Final Report 3/4
15:47:50	2001 Profit Announcement - Full Year Result 15/19
15:52:29	Preliminary Final Report 2/4

Time	SGB Announcements-7th November 2001
10:26:26	SGB - Preliminary Final Report 11/15
10:29:33	SGB - Preliminary Final Report 6/15
10:51:53	SGB - Preliminary Final Report 12/15
11:02:33	SGB - Preliminary Final Report 4/15
11:11:44	SGB - Preliminary Final Report 13/15
11:45:54	SGB - Preliminary Final Report 14/15
12:12:41	SGB - Preliminary Final Report 9/15
12:14:59	SGB - Preliminary Final Report 7/15
14:06:21	SGB - Preliminary Final Report 10/15
14:08:53	SGB - Preliminary Final Report 15/15
	WBC Announcements-2th November 2001
10:29:06	Westpac delivers strong profit results 1/5
10:40:00	Westpac delivers strong profit results 2/5
10:50:21	Profit Announcement 1/5
11:05:02	Media Release Westpac delivers strong profit results 1/1
11:26:18	Westpac delivers strong profit results 4/5
11:37:12	Preliminary Final Report 2/6
11:54:06	Westpac delivers strong profit results 3/5
12:11:13	Preliminary Final Report 3/6
12:13:19	Westpac delivers strong profit results 5/5
12:23:20	Profit Announcement 2/5
12:26:44	Profit Announcement 4/5
12:57:57:	Profit Announcement 3/5
12:10:01	Profit Announcement 5/5
13:36:21	Intention to declare dividend
13:48:18	Appendix 3B - Exercise of Options
15:23:24	HPL becoming a substantial shareholder from WBC

The denominator of the fractions indicate the total number of documents being released, whilst the numerator indicates which document from the total is being released to the market.

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