A Continuous-Time Measurement of the Buy-Sell Pressure in a Limit Order Book Market

Anthony D. Hall

School of Finance and Economics

University of Technology, Sydney

Nikolaus Hautsch*

Institute of Economics

University of Copenhagen

September 30, 2004

Abstract

In this paper, we investigate the buy and sell arrival process in a limit order book market. Using an intensity framework allows to estimate the simultaneous buy and sell intensity and to derive a continuous-time measure for the buy-sell pressure in the market. Based on limit order book data from the Australian Stock Exchange (ASX), we show that the buy-sell pressure is particularly influenced by recent market and limit orders and the current depth in the ask and bid queue. We find evidence for the hypothesis that traders use order book information in order to infer from the price setting behavior of market participants. Furthermore, our results indicate that the buy-sell pressure is clearly predictable and is a significant determinant of trade-to-trade returns and volatility.

Keywords: buy and sell arrival process, order book information, market depth, bivariate autoregressive intensity model, buy-sell excess intensity

JEL Classification: G14, C32, C41

*Corresponding author. Email: Nikolaus.Hautsch@econ.ku.dk. Address: Studiestraede 6, University of Copenhagen, DK-1455 Copenhagen-K, Denmark, tel: ++ 45 35323022, fax: ++ 45 35323000. *Acknowledgements*: Earlier versions of this paper have been presented at the conference on "New Frontiers in Financial Volatility Modelling", Florence, 2003, the 2003 ESEM conference in Stockholm and the program "Econometric Forecasting and High-Frequency Data Analysis", Singapore, 2004. For valuable comments we would like to thank Rob Engle, Søren Johansen, Gaëlle LeFol, Neil Shephard, and the participants of the the faculty seminar at UTS, the econometrics seminar at CREST, Paris, and the faculty seminar at the University of Copenhagen. Furthermore, helpful comments were received while Nikolaus Hautsch was visiting the Institute for Mathematical Sciences, National University of Singapore and the Singapore Management University in 2004. Special thanks are due to James McCulloch whose assistance in preparing the data has made this research project feasible. The paper was conceived when Nikolaus Hautsch was a Visiting Fellow at UTS, and in this context he would like to thank UTS for financial support.

1 Introduction

Computerized trading systems are of growing importance on financial markets worldwide. Over the past fifteen years, numerous exchanges have reorganized their trading systems and replaced the traditional floor trading by fully electronic trading systems. This development has inspired an increasing interest in the theoretical and empirical implications of such trading systems, and in particular, the availability of detailed information on the complete order flow in a market has created a new exciting field of research in empirical finance.

Limit order book data can be regarded as the informational limit case which provides detailed characteristics about the complete order process and allows the study of a plethora of questions, that cannot be analyzed using traditional transaction data bases. An important objective in this field of research is to study the informational content of the limit order book, as well as traders' order submission strategies and the determinants and characteristics of order aggressiveness.[1] This research is essential to obtain a better understanding of how traders' behavior is influenced by the current state of the market. Gaining deeper insights into the relationship between the state of the order book and the time-varying liquidity supply and demand is particularly important in order to judge the performance and effectiveness of a trading system.

The major objective of this study is to analyze in a limit order book market the determinants of the buy intensity, the sell intensity, and the resulting buy-sell pressure. The main contribution and novel feature of this paper is to study these issues in a dynamic continuous-time framework. Modelling the buy and sell arrival process with a bivariate dynamic intensity model provides an estimate of the *simultaneous* buy and sell intensity in each instant of time. The major advantage of this approach is that no aggregation over time is required and the method can account for all limit order arrivals between consecutive transactions. Hence, the proposed framework enables continuous-time modelling of a traders' decision of *when to trade* and *on which side of the market to trade* while taking into account any changes in the limit order book and incorporating the (multivariate) dynamics of the buy and sell arrival processes. This approach is a very natural and powerful way to study order book dynamics on a completely disaggregated level and is superior to the (non-dynamic) methods for qualitative dependent variables recently used by Al-Suhaibani and Kryzanowski (2000), Griffiths, Smith, Turnbull, and White (2000), Hollifield, Miller, Sandås, and Slive (2002) or Ranaldo (2004). Moreover, the intensity framework allows the measurement of imbalances between both sides of the market on the lowest aggregation level. In this context, the difference between the estimated simultaneous buy and sell intensity yields a readily interpretable measure of the permanent buy-sell pressure in the market. Such a measure allows the characterization of market periods in which traders have a strong preference for one-sided trading.

In this methodological framework, we address the following related research questions: (i) Does the current state of the limit order book influence the buy intensity, the sell intensity, and the buy-sell pressure in the market? (ii) Do traders exploit information about the market from the limit order book

[1] See *inter alia* Harris and Hasbrouck (1996), Harris (1998), Bisière and Kamionka (2000), Griffiths, Smith, Turnbull, and White (2000), Hollifield, Miller, Sandås, and Slive (2002), Zovko and Farmer (2002), Beber and Caglio (2003), Lo and Sapp (2003), Linnainmaa (2003), Cao, Hansch, and Wang (2003), Winne and D'Hondt (2003) or Ranaldo (2004).

or do they primarily exploit periods of high liquidity, i.e., when the trading on one particular side of the market becomes cheaper? (iii) Is the buy (sell) intensity mainly driven by the order book on the same side of the market or are there interdependencies between both sides of the market? (iv) Is the buy-sell pressure predictable and what influence does it have on the trade-to-trade return process? Moreover, are strong buy-sell imbalances a major source of trade-to-trade volatility?

Probably one of the most interesting objectives in the literature on order driven markets is the reconstruction of the limit order book, and thus, the demand and supply curve at each instant of time. Nevertheless, to our knowledge, only a few current databases allow for a distinct reconstruction of the *complete* limit order book. Many data sources suffer from their incompleteness due to the existence of hidden orders or iceberg orders (see for example Biais, Hillion, and Spatt, 1995 regarding the order book at the Paris bourse). In these cases the actual order book can only approximated. Here, we use an unique data set extracted by replicating the fully automatized execution engine of the Australian Stock Exchange (ASX), which allows not only for an exact identification of buyer or seller initiated trades, but also for a complete and distinct reconstruction of the order book at each instant of time. Based on this data, it is possible to quantify the buy and sell intensity and their the dependence from different states of the market, as characterized by the standing buy and sell volume, the ask and bid depth or imbalances between the buy and sell side.

Our methodological framework is based on the concept of the (stochastic) intensity function which is defined as the instantaneous event arrival rate and is a powerful way to model multivariate point processes. Since it is a continuous-time concept, it allows us to overcome the problem that the buy and sell transactions are not equally spaced in time and may occur asynchronously. In this sense, a multivariate intensity approach is superior to competing risks settings as applied, for example, by Bisière and Kamionka (2000), Coppejans and Domowitz (2002), Hollifield, Miller, Sandås, and Slive (2002) or Lo and Sapp (2003). The main disadvantage of these approaches is that only one single process can be modelled completely, whereas all other processes have to be treated as censored which naturally results in a loss of important information. Here, we apply a bivariate version of the so-called autoregressive conditional intensity (ACI) model which was proposed by Russell (1999). This approach not only enables the measurement of the trading intensity on both market sides simultaneously, but also the interdependencies between the buy and sell side. We extend the ACI model to account for the changes in the limit order book that occur whenever a limit order enters the market. Since limit orders naturally arrive during the interval between two consecutive trades, these order book and limit order characteristics have to be modelled as time-varying covariates.

Our empirical analysis consists of two parts. In the first part, we analyze the determinants of the buy and sell intensity. Based on the estimates of a bivariate ACI model for the buy and sell process, we can summarize the following main results: First, it is shown that the buy and sell intensity, evaluated at the point in time of each individual transaction, follow highly positively autocorrelated processes with strong cross-autocorrelations. This establishes clear evidence for spill-over effects between both sides of the market. Second, the buy and sell intensity and the resulting buy-sell pressure are significantly influenced by the current depth on the bid and ask side, market tightness, as well as the characteristics of the most recent market and limit orders. We find evidence that the buy-sell pressure increases (decreases) when the ask (bid) side reflects a higher dispersion of posted limit prices. These results show that the order book conveys information regarding traders' price setting behavior which permits inference with respect to expected price movements. Third, we find clear evidence for interdependencies between both market sides. Thus, traders' preference for immediacy on one particular market side is not only influenced by characteristics of the same side, but also by the opposite side.

The second part of the empirical study is devoted to the analysis of the relationship between the buy-sell pressure and the intraday return process. We show that the buy-sell pressure, evaluated at the points in time of individual trades, follows a positively autocorrelated persistent process indicating clear predictability of this variable. By including the excess buy intensity as a regressor in an ARMA-GARCH model for trade-to-trade returns, it is shown that the current buy-sell pressure has significant predictable power for trade returns and volatility even when we control for the influence of variables capturing the state of the market. Hence, we identify the buy-sell pressure as an important determinant of intraday trading activity. These findings illustrate the importance of studying such effects on a completely disaggregated level.

The remainder of the paper is organized in the following way: In Section 1 we discuss the economic rationales behind determinants of the buy-sell pressure in the market. Section 2 presents the methodological framework. In Section 3 we describe the data base and the corresponding explanatory variables. Section 4 presents the empirical results, while Section 5 concludes.

2 Determinants of the Buy-Sell Pressure

In this section, we discuss the main results in the recent theoretical and empirical literature on the informational content of the limit order book and trader's order submission strategies. By systematizing the major implications of this literature, we motivate several testable propositions concerning the economic determinants of the buy-sell pressure in the market.

Traditional information-based market microstructure models rest on the assumption of heterogeneous groups of traders. In a large section of the literature[2] it is assumed that the trading process is driven by the interaction between 'informed traders', who trade due to private information and 'liquidity traders', who trade due to exogenous (liquidity) reasons. The main idea of these approaches is that uninformed market participants infer the existence of information from the trading process. For this reason, market microstructure variables like the price change, the bid-ask spread, the trading volume and the trading intensity provide information about the state of the market. However, in order driven markets, traders infer the existence of information not only from the trading process but also from the complete order arrival process and the state of the order book. Numerous studies focus on the informativeness of market orders and limit orders. A common belief in many studies (see for example Glosten, 1994, Seppi, 1997, Harris, 1998 or Linnainmaa, 2003) is that market orders are more informative than limit orders. This argument arises from the classical market microstructure literature where informed traders tend to exploit

[2]See, for example, Glosten and Milgrom (1985), Kyle (1985), Diamond and Verrecchia (1987) or Easley and O'Hara (1992).

their informational advantage and prefer market orders as they guarantee immediate execution.

In this literature, several papers draw particular attention to the informational role of the trading volume. Easley and O'Hara (1987) show that the transaction volume is a strong proxy for the existence of information on the market. Blume, Easley, and O'Hara (1994) illustrate that the volume provides additional information that cannot be deduced from price statistics. Accordingly, large buy (sell) trading volumes serve as positive (negative) price signals and thus should increase a traders' preference to execute a buy (sell) market order. On the other hand, trading a large volume reduces the depth on the corresponding market side. Several studies (see for example Griffiths, Smith, Turnbull, and White, 2000, and Beber and Caglio, 2003) have found evidence that traders tend to submit market orders in situations where the depth on the same (opposite) side is large (small). According to these findings, large volumes reduce traders' preference for immediacy on the corresponding side of the market. Hence, arguments relying on the informational content of volume stand in sharp contrast to arguments based on liquidity. In order to test these conflicting implications, we formulate the following proposition in favor of the informational role of the trading volume:

P1: Buy and sell trading volumes

Large buy (sell) transaction volumes increase (decrease) the buy-sell pressure.

While the current trading volume is associated with a *flow* variable, the total volume standing in the ask and bid queue is a *stock* variable that characterizes the current aggregate demand and supply in the market. Differences between buy and sell aggregates reflect buy-sell order imbalances which are recognized as important sources of intraday trading activity (see for example Chan and Fong, 2000, Chordia, Roll, and Subrahmanyam, 2002, and Lee, Liu, Roll, and Subrahmanyam, 2003). However, similar to the arguments above, imbalances between the bid and the ask side, on one hand, reveal signals regarding information in the market, but on the other hand, imply contrary liquidity effects. To clarify this issue, consider a market situation characterized by an increasing volume on the ask side. Given the bid side, we observe an increasing net supply, i.e. traders post more ask quotes indicating an increasing preference for sells rather than for buys which may be interpreted as 'bad' news. Hence, according to this argument, a trader who infers expected price movements from the limit order book would sell. This argument is consistent with the recent findings of Bloomfield, O'Hara, and Saar (2002) and Cao, Hansch, and Wang (2003) who illustrate that informed traders are not mainly 'liquidity takers' but tend to utilize limit orders more than liquidity traders. An important implication of this behavior is that queued limit orders have informational value. However, on the other hand, a higher volume on the ask side increases the liquidity on this side of the market. A (liquidity) trader who wants to buy is confronted with smaller price impacts and thus lower liquidity costs. Hence, he would tend to exploit this situation and increase his preference to execute a buy transaction. Evidence in favor of this argument was found by Griffiths, Smith, Turnbull, and White (2000) and Beber and Caglio (2003). Therefore, again liquidity arguments lead to conflictive implications. Nevertheless, we formulate the next proposition in terms of the information content argument:

P2: Imbalances between total ask and bid volumes

An increase of the total ask (bid) volume decreases (increases) the buy-sell pressure.

Note that the total volume in the bid and ask queue does not permit any conclusions regarding the depth on the particular market sides. A more precise assessment of the market depth is revealed by the steepness of the market reaction curve that relates the cumulated buy/sell volume to the corresponding limit ask/bid prices (see Figure 1 in the Appendix). The steeper the market reaction curve, the lower the price impact of any hypothetical volume, and as a result, the lower the liquidity costs. However, regarding the influence of the market depth on the buy-sell pressure in the market, the same logic discussed above applies. A lower ask (bid) depth reflects a higher dispersion of prices in the ask (bid) queue and thus, indicates that traders are willing to sell (buy) their positions at comparatively higher (lower) prices which indicates positive (negative) price signals and as such increases (decreases) the buy-sell pressure. However, at the same time, a lower ask (bid) depth increases the price impact of any hypothetical buy (sell) volume which decreases (increases) the net buy intensity. Following the first argument, we consider proposition P3 as follows:

P3: Imbalances between ask and bid slopes

An increase in the ask (bid) depth decreases (increases) the buy-sell pressure.

Numerous studies focus on the inside spread, defined as the spread between the current best bid and best ask price, as a measure for the tightness of the market (see for example Cohen, Maier, Schwartz, and Whitcomb, 1981, Niemeyer and Sandås, 1995, Wang, 1999, Declerck, 2000, Duffie and Ziegler, 2001, Handa, Schwartz, and Tiwari, 2003 and McCulloch, 2003). In a market-maker market, the spread compensates market-makers for the risk of adverse selection and thus is positively correlated with the existence of market information (see for example Stoll, 1989, Easley and O'Hara, 1992 and Huang and Stoll, 1997). Therefore, several market microstructure theories predict a positive relationship between the magnitude of the spread and the trading intensity. However, in a limit order book market, a high spread decreases market liquidity since the crossing from one market side to the other market side is more expensive. Hence, we expect a negative impact on the trading intensity on both sides of the market, which is confirmed for example by Griffiths, Smith, Turnbull, and White (2000). However, since the width of the spread provides no price signal, we do not expect an influence on the excess buy-sell intensity which leads to the following proposition:

P4: Bid-ask spread

A higher spread decreases the trading intensity on both sides of the market, but has no impact on the buy-sell pressure.

The final proposition deals with the impact of past (signed) mid-quote changes. This variable reflects past trading or quote activities leading to changes in the best bid or ask prices. For instance, large negative mid-quote changes are caused either by the arrival of a sufficiently large sell market order or an ask order with a limit price that shifts the current best ask price downwards. Both events indicate, on one hand, 'bad' expectations with respect to future price movements, or in contrast, an increasing depth on the ask side compared to the bid side. Emphasizing the information argument leads to proposition P5.

P5: Midquote changes

A negative (positive) midquote change decreases (increases) the buy-sell pressure.

The propositions P1 through P5 build the economic arguments behind the explanatory variables used in the empirical analysis in Section 5. Consideration of the signs of the respective estimated regression coefficients will provide deeper insights into the underlying question of whether traders monitor the current state of the order book in order to exploit situations where the execution of a particular market order is favorable, or whether they infer market information from the limit order settings.

3 Modelling Autoregressive Multivariate Point Processes

The random and asynchronous occurrence of buys, sells and limit orders is statistically described in terms of a multivariate point process. A natural way to model multivariate point processes is to adopt an intensity approach that allows point processes to be modelled in a continuous-time framework. The main advantage of specifying the intensity function instead of the durations between consecutive points is that it allows to consider changes of the information set, like the occurrence of an event in any other process or the change of a (time-varying) regressor, at *any* point in time. In this context, dynamic intensity models are more powerful than discrete time autoregressive duration models (see e.g. Engle and Russell, 1998) since in these models, one typically conditions only at the beginning of the corresponding duration spell. A detailed discussion of the advantages and disadvantages of both model frameworks is found in Hautsch (2004).

3.1 Notation

Let t denote the physical or calendar time. In the following, we define a K-dimensional point process with the sequence of arrival times $\{t_i^k\}_{i=1}^{n^k}$ of the individual processes $k = 1, \dots, K$. Furthermore, let $N^k(t) = \sum_{i \geq 1} \mathbb{1}_{\{t_i^k \leq t\}}$ represent the *right-continuous* counting function that counts all points occurring before and including t. Correspondingly, $M^k(t) = \sum_{i \geq 1} \mathbb{1}_{\{t_i^k < t\}}$ denotes the *left-continuous* counting function that counts all k-type points that occurred *before* t. Accordingly, $N(t)$ and $M(t)$ are defined as the right-continuous and left-continuous counting function, respectively, of the *pooled* process $\{t_i\}_{i=1}^n$, which pools and orders the arrival times of *all* K individual processes. Moreover, the process $x^k(t)$ with $x^k(t) = t - t_{M^k(t)}^k$ is called the *backward recurrence time* at t associated with the k-th process. The backward recurrence time is the time elapsed since the previous point and is a left-continuous function that grows linearly through time with discrete jumps back to zero instantaneously *after* each arrival time t_i^k.

Let $\{z_i\}_{i=1}^n$ be the sequence of marks corresponding to the characteristics associated with the arrival times t_i. Marks can be interpreted as time-invariant covariates, that are only observable at the particular points t_i and that do not change between the two points t_{i-1} and t_i. Furthermore, we assume the existence of a so-called time-varying covariate process[3] which occurs at discrete points $t_1^0, t_2^0, \ldots, t_{n^0}^0$. Then, $N^0(t)$ and $M^0(t)$ denote the corresponding right-continuous and, respectively, left-continuous counting processes associated with the arrival times of the covariate process $z_{N^0(t)}^0$. Moreover, let $\{\tilde{t}_i\}$ be the pooled process of *all* points t_i and t_i^0.

In the following we assume that the pooled process $N(t)$ is orderly, i.e.

$$\Pr\left[(N(t+\Delta) - N(t)) > 1 \,|\mathcal{F}_t\right] = o(\Delta),$$

where $o(\Delta)$ denotes a remainder term with the property that $o(\Delta)/\Delta \rightarrow 0$ as $\Delta \rightarrow 0$ and $\mathcal{F}_t$ denotes the history of the process up to and including t. Under this assumption, all individual K $(k = 1, \ldots, K)$ univariate point processes are also orderly.

3.2 The Concept of the Intensity Function

A central concept in the theory of point processes is the intensity function. Let $N^k(t)$ be a simple point process associated with k-type events on $[0, \infty)$ that is adapted to some history $\mathcal{F}_t$ and assume that $\lambda^k(t; \mathcal{F}_t)$ is a positive process with sample paths that are left-continuous and have right-hand limits. Then, the process

$$\lambda^k(t; \mathcal{F}_t) := \lim_{\Delta \downarrow 0} \frac{1}{\Delta} \mathrm{E}\left[N^k(t+\Delta) - N^k(t) \middle| \mathcal{F}_t \right], \qquad \lambda^k(t; \mathcal{F}_t) > 0, \; \forall \, t, \tag{1}$$

is called the $\mathcal{F}_t$-intensity process of the counting process $N^k(t)$. Hence, the $\mathcal{F}_t$-intensity process characterizes the evolution of the point process $N^k(t)$ conditional on some history $\mathcal{F}_t$. Under the assumption of Equation (1), the intensity function can be also be written as

$$\lambda^k(t; \mathcal{F}_t) = \lim_{\Delta \downarrow 0} \frac{1}{\Delta} \Pr\left[(N^k(t+\Delta) - N^k(t)) > 0 \,|\mathcal{F}_t \right], \tag{2}$$

which can be heuristically interpreted as the conditional probability per unit time of observing an event in the next instant, given the conditioning information.

Furthermore, define

$$\Lambda^k(t_{i-1}^k, t_i^k) := \int_{t_{i-1}^k}^{t_i^k} \lambda^k(s; \mathcal{F}_s) ds \tag{3}$$

as the *integrated intensity function* associated with the k-type process. The integrated intensity function is an important concept to derive diagnostics for point processes. Bowsher (2002) proves that, under the fairly weak assumption

$$\int_0^\infty \lambda^k(t; \mathcal{F}_t) dt = \infty, \tag{4}$$

[3]Here, such a process characterizes the arrival of new limit orders in the market.

the integrated intensity function follows an i.i.d. standard exponential process, thus

$$\Lambda^k(t_{i-1}^k, t_i^k) \sim \text{i.i.d. } \operatorname{Exp}(1). \tag{5}$$

This relationship provides a valuable basis for diagnostic tests against misspecification of the intensity function. Moreover, $\Lambda^k(t_{i-1}^k, t_i^k)$ can be interpreted as a generalized error (for example, in the spirit of Cox and Snell, 1968) and indicates whether the path of the conditional intensity function under-predicts $(\Lambda(t_{i-1}^k, t_i^k) > 1)$ or over-predicts $(\Lambda^k(t_{i-1}^k, t_i^k) < 1)$ the number of events between t_{i-1}^k and t_i^k.

3.3 Autoregressive Conditional Intensity Models

Dynamic intensity models can be modelled in two general ways. The first possibility is to parameterize the intensity function in terms of an autoregressive process that is updated at each occurrence of a new point. Following this strategy, Russell (1999) proposes a dynamic extension of a proportional intensity model that he calls autoregressive conditional intensity (ACI) model. An alternative is to assume that the intensity function is driven by a function of the backward recurrence time to all previous points leading to a so-called self-exciting process (see Hawkes, 1971, and more recently Bowsher, 2002)[4]. However, here we follow the first strategy and specify an ACI model that allows to account for time-varying covariates.

In the following we define the multivariate intensity function as

$$\lambda(t; \mathcal{F}_t) = \begin{bmatrix} \lambda^1(t; \mathcal{F}_t) \\ \lambda^2(t; \mathcal{F}_t) \\ \vdots \\ \lambda^K(t; \mathcal{F}_t) \end{bmatrix}, \tag{6}$$

where each component is parameterized as

$$\lambda^k(t; \mathcal{F}_t) = \Psi^k(t) \lambda_0^k(t) s^k(t), \qquad k = 1, \ldots K, \tag{7}$$

and $\Psi^k(t)$ is a function that captures the dynamics of the k-type process while $\lambda_0^k(t)$ denotes a k-type baseline intensity component that is parameterized according to a predetermined distribution. Furthermore, $s^k(t)$ is a k-type seasonality component that may be specified using a spline function.

Russell (1999) proposes specifying $\Psi^k(t)$ as[5]

$$\Psi^k(t) = \exp\left(\tilde{\Psi}_{M(t)+1}^k + z_{M(t)}' \gamma^k + z_{M^0(t)}^{0\prime} \tilde{\gamma}^k\right), \tag{8}$$

where the vector $\tilde{\Psi}_i' = \left(\tilde{\Psi}_i^1, \tilde{\Psi}_i^2, \ldots, \tilde{\Psi}_i^K\right)$ is parameterized in terms of a VARMA type specification, given by

$$\tilde{\Psi}_i = \sum_{k=1}^{K} \left(A^k \breve{\epsilon}_{i-1} + B \tilde{\Psi}_{i-1}\right) y_{i-1}^k, \tag{9}$$

with $A^k = \{\alpha_j^k\}$ denoting a $(K \times 1)$ vector associated with the scalar innovation term and $B = \{\beta_{ij}\}$ a $(K \times K)$ matrix of persistence parameters. Furthermore, y_i^k defines an indicator variable that takes

[4]See Hautsch (2004) for more details.

[5]For ease of illustration, we restrict our consideration to a lag order of one. The extension to higher order specifications is straightforward.

the value 1 if the i-th point of the pooled process is of type k, whereas γ and γ_0 respectively, are the coefficient vectors associated with the marks and the time-varying covariates.

The scalar innovation term $\breve{\epsilon}_{M(t)}$ is based on the log integrated intensity associated with the most recently observed process, thus

$$\breve{\epsilon}_i = \epsilon_i^{k*} y_i^k, \tag{10}$$

where

$$\epsilon_i^{k*} := 1 - \Lambda^k(t_{i-1}^k, t_i^k) \tag{11}$$

denotes the k-type innovation term with

$$\Lambda^k(t_{i-1}^k, t_i^k) = \sum_j \int_{\tilde{t}_j^k}^{\tilde{t}_{j+1}^k} \lambda^k(u; \mathcal{F}_u) du, \tag{12}$$

and j indexes all points with $t_{i-1}^k < \tilde{t}_j \leq t_i^k$.

Hence, Equation (9) implies a regime-switching structure since A^k is a vector of coefficients reflecting the impact of the innovation term on the intensity of the K processes when the previous point ($t_{M(t)}$) was of type k. Since we assume that the process is orderly so that only one type of point can occur at any instant, the innovation $\breve{\epsilon}_i$ is a scalar random variable and is associated with the most recently observed process. Note that since $\breve{\epsilon}_i$ is based on a mixture of i.i.d. random variables, it is also an i.i.d. process. For this reason, weak stationarity of the model depends on the eigenvalues of the matrix B. If the eigenvalues of B lie inside the unit circle, the process $\tilde{\Psi}_i$ is weakly stationary. Moreover, our simulation studies strongly support the hypothesis that $\mathrm{E}[\breve{\epsilon}_i] = \mathrm{E}[\epsilon_i^{k*}]$, so that it is reasonable to center the innovation terms as in Equation (11).

The baseline intensity function $\lambda_0^k(t)$ may be specified using a multivariate Burr-type parameterization, i.e.,

$$\lambda_0^k(t) = \exp(\omega^k) \prod_{r=1}^{K} \frac{x^r(t)^{p_r^k - 1}}{1 + \kappa_r^k x^r(t)^{p_r^k}}, \ (p_r^k > 0, \ \kappa_r^k \geq 0). \tag{13}$$

A special case occurs when the k-th process depends only on its own backward recurrence time, in which case $p_r^k = 1$ and $\kappa_r^k = 0$, $\forall\, r \neq k$.

Denote W as the data matrix consisting of all points, marks and covariates. Then, the log likelihood function of the multivariate ACI model is computed as

$$\ln \mathcal{L}(W; \theta) = \sum_{k=1}^{K} \sum_{i=1}^{n} \left\{ -\Lambda^k(t_{i-1}, t_i) + y_i^k \ln \lambda^k(t_i; \mathcal{F}_{t_i}) \right\}, \tag{14}$$

where $\Lambda^k(t_{i-1}, t_i)$ is computed by

$$\Lambda^k(t_{i-1}, t_i) = \sum_j \int_{t_{i-1}}^{t_i} \lambda^k(u; \mathcal{F}_u) du, \tag{15}$$

where j indexes all points with $t_{i-1} \leq \tilde{t}_j \leq t_i$. Hence, $\Lambda^k(t_{i-1}, t_i)$ has to be computed by piece-wise integration over one spell, where the pieces are determined by the arrival of the time-varying covariates.

According to Equation (5), under correct specification the residuals, $\hat{\varepsilon}_i^k$ should be distributed as i.i.d. unit exponential. Hence, model evaluation can be done by testing the dynamic properties of the residual series using for example the Ljung-Box statistic, and by testing the distribution properties. For instance, Engle and Russell (1998) propose a test against excess dispersion based on the asymptotically normal test statistic $\sqrt{n^k/8}(\hat{\sigma}^2_{\varepsilon^k} - 1)$, where $\hat{\sigma}^2_{\varepsilon^k}$ is the empirical variance of the residual series.

4 The Data

4.1 The Australian Stock Exchange

The Australian Stock Exchange (ASX) is a continuous double auction electronic market with business (trading) rules similar to other electronic limit order markets such as Paris, Hong Kong and Sao Paulo. The continuous auction trading period is preceded and followed by an opening call auction. The exact opening times are randomized from 10:00 am, but normal trading takes place continuously on all stocks between 10:09 am and 16:00 pm from Monday to Friday. The market is opened with a call auction market in all stocks. Before the call market opens, traders are allowed to enter public quotes from 07:00 am until the call auction completes and the market is opened for continuous trading. An overview of the trading rules is given in Table I.[6]

4.2 Normal Market Trading at the ASX

A comprehensive description of the trading rules of the Stock Exchange Automated Trading System (SEATS) on the ASX can be found in the SEATS Reference Manual (available at www.asxonline.com). A simplified summary description of the major features of the electronic double auction market during normal market trading follows below.

4.2.1 Limit Orders, Market Orders and Aggregated Trades

When the ASX is in normal open mode (10:09-16:00), any buy (sell) order entered that has a price that is greater (less) than existing queued sell (buy) orders, will execute immediately. Trades will be generated and traded orders deleted until there is no more sell (buy) order volume that has a price that is equal to or less than the entered buy (sell) order. Orders that execute immediately are *market orders.* Queued orders (orders entered with a price that does not overlap the opposite order queue) are *limit orders.* Entered orders that partially execute are a *combination* of a market order for the immediately executed volume and a limit order for the remaining volume. When a market order executes against limit orders, the ASX generates a trade record for each market order - limit order pair of executing orders. As a result, if a market order executes against several limit orders, several trade records are generated. However only one logical trade has been executed, and for the empirical research reported here, the multiple trade records generated by a single market order are aggregated into a single trade record.

[6] All tables and figures are given in the Appendix.

4.2.2 Price, Time Priority Rules

Limit orders are queued in the buy and sell queues according to a strict price-time priority order. Between 7:00 am and 17:00 pm, orders may be entered, deleted and modified without restriction. Modifying order volume downwards does not affect order priority. Modifying order volume upwards automatically creates a new order at the same price as the original order with the increase in volume recorded as the volume of the newly created order. This avoids loss of priority on the existing order volume. Modifying order price so that price overlaps the opposite order queue will cause immediate or partial execution of the order according to the rules listed above (the order is converted to a market order or a market and limit order combination). Modifying price otherwise causes the order to move to the lowest time priority within the new price level.

4.2.3 Market Information Visibility

All previous and current orders and trades are always visible to the public. Order prices are always visible, however orders may be entered with an undisclosed or hidden volume if the total value of the order exceeds $200,000. Although undisclosed volume orders are permitted, sufficient information is available to unambiguously reconstruct all transactions. The identity of the broker who entered an order is not public information, but is available to all other brokers. The efficiencies generated by moving to electronic trading and settlement systems mean that the ASX no longer requires minimum lot sizes to be traded in any stock and single share orders are common.

4.2.4 Minimum Tick Size

The minimum tick size for order prices below $0.10 is $0.001, for order prices above $0.10 and below $0.50 is $0.005, while the minimum tick size for stock orders priced $0.50 and above is $0.01.

4.2.5 Special Trades

If brokers have a matching buy or sell order they may 'cross' this order in the market. Crossings do not participate in the market because the broker provides both the buy and sell volume in the crossing, the buy and sell limit order queues are unchanged and the trade generated is reported with a special crossing parameter. Crossings should not be confused with the situation where the same broker is both buyer and seller in the normal course of trading, as in this case the limit order queues are modified by the trade execution in the usual way. Trades reported to the market that are not executed through the SEATS system are designated 'Off-Market Trades'. There are three main generators of these off-market trades, late and overnight trading, reporting trades from the 'upstairs' telephone market and reporting the exercise of in-the-money exchange traded options which are stock settled. Trades reported from the 'upstairs' phone market do not participate in the price discovery process and may be priced away from the current market. These trades are called specials and must have a value greater than $2,000,000. It is a requirement that these trades be reported immediately to the market, however there is no practical way for the ASX to enforce this rule. These trades are executed by private negotiation between the brokers and their institutional clients.

4.2.6 Data Extraction

The data that is extracted from the SEATS system using customized software contains time stamped prices, volumes and identification attributes of all transactions, market and limit orders, and reconstructs the state of the order book at any time. We extract samples consisting of all trades and limit orders during the normal trading period for all trading days of July 2002. Data from the opening and closing call auctions periods are not utilized and all crossing and off market trades are removed. The limit order arrival during two consecutive trades is captured by time-varying covariates. In this context, we are able to summarize the changing state of the order queues as a result of the arrival of new limit orders or amendments to existing orders.

4.3 Explanatory Variables

The empirical analysis reported here is based on three stocks traded on the ASX: The National Australian Bank (NAB), a banking and financial services company; BHP Billiton Limited (BHP), a large diversified resource company; and Mount Isa Mines Limited (MIM), a base metal mining company. The sample period covers all twenty-four trading days in July 2002 leading to $58,808$, $73,893$ and $12,546$ observations for NAB, BHP and MIM, respectively.

Table III presents descriptive statistics associated with observations on the trade and limit order arrival processes considered in this study. We observe mean trade durations of 20 seconds for NAB, of 17 seconds for BHP, and 122 seconds for MIM, respectively. This indicates a relatively high trading activity for both NAB and BHP whereas for MIM, a clearly lower liquidity is observed. During the analyzed sample period, for both NAB and BHP we find more buy trades than sell trades associated with upward price movements. In contrast, for the MIM stock we observe declining prices as a result of substantially more sell trades than buy trades. For all stocks, the Ljung-Box statistics reveal a significant autocorrelation and quite strong persistence in both the trade process and the limit order process. This is a well known phenomenon for financial point processes (see, for example, Hautsch, 2004).

According to the economic considerations discussed in Section 2, we generate three groups of explanatory variables. Table II gives a precise definition of the individual covariates used in this empirical study. The first category contains variables that capture information from the previous day. Though inter-day effects are ignored in most empirical studies based on high-frequency data, there exists some empirical evidence confirming spill-over effects between consecutive trading days (see for example, Bowsher, 2002). In order to account for such influences, we include the difference between the aggregated volume traded in the previous day's closing auction and in the current day's opening auction (CLOPVOL). Correspondingly, we generate the difference between the previous day's closing price and the current opening price (CLOPPR) as an indicator for expected price movements. Furthermore, as a variable to account for possible trading imbalances on the previous day, we include the difference between the total bid and ask volume recorded at the closure of the normal market period on the preceding day (CLBA). Note that these three variables are regressors that change only from day to day. The second category contains variables that are observed only at each particular trade. Here, we use the trading volume at the previous trade interacted with a buy/sell indicator (TRVB, TRVS). The third group consists of variables that are recorded whenever a new order arrives in the market and which are measured as time-varying covariates. In order to capture the aggregated supply and demand on the market, we continuously record the aggregated trading volume on the bid and ask sides of the market (AVOL and BVOL). Note that these volumes are determined by the standing volume of the previous day, the pre-opening and opening procedures, incoming market orders, as well as posted, changed and cancelled limit orders during a day. In this sense, at any time they reflect the overall current aggregated demand and supply in the market. Furthermore, differences between limit prices associated with certain volume quantiles on the bid and ask side allow us to compute the (piecewise) slope of the market reaction curve (ASK_x, BID_x) as a measure for the (piecewise) depth of the market. For a graphical illustration of these measures, see Figure 1. Based on these quantiles, it is possible to identify the potential price impact caused by a buy/sell market order. As a measure for the tightness of the market, we use the spread between the current best bid and best ask price (SPRD). In order to control for the influence of recent orders, we include the type of the current limit or market order (QASK), as well as the most recent mid-quote price change (DMQ).

In order to provide an impression regarding the magnitudes and intradaily variations of these variables, Figures 2 through 4 show intraday seasonality plots, based on cubic spline regressions using one hour knots. We observe clear seasonality patterns which are mainly driven by opening, lunchtime and closing effects. Interestingly, for all three stocks we find substantially higher aggregated volumes on the ask side compared to the bid side. Naturally, the total ask and bid volumes increase over any particular day. Regarding the steepness of the market reaction curve, on both sides of the market we observe relatively symmetric patterns. Nevertheless, there is weak evidence for a slightly higher depth on the ask side.

5 Empirical Results

5.1 Determinants of the Buy/Sell Intensity

5.1.1 Statistical Properties of the Buy/Sell Intensity

Tables IV through VI present the estimated parameters of bivariate ACI models with static and time-varying covariates. Note that all regressors are weakly exogenous for the intensity function since they enter the model in lagged form (recall Equation (8)). The lag order of the models are chosen according to the BIC leading to an ACI(1,1) parameterization as the best specification for all three series. We standardize the time scale by the average duration of the pooled process.[7] The persistence matrix B is fully specified, implying interdependence of the persistence terms between both processes. The baseline intensity function is specified using the Burr form as in Equation (13). The seasonality functions for both the buy and sell series are modelled using joint linear spline functions based on 1 hour nodes.[8] Figure 6 shows the estimated intraday seasonality functions for all three stocks. The functions imply relatively high intensity functions near the opening and closing of trade. Around noon, we observe the typical 'lunch time dip' associated with a significant decline in trading activity. This effect is well documented

[7]Note that this scaling does not change the order of the processes.

[8]We also estimated the models with individual spline functions for the buy and the sell process, however, as we found similar seasonality patterns for both types of trades we report the more parsimonious specification.

in many studies analyzing transaction data (see, for example Hautsch, 2004).

For each stock, we estimate three specifications. Column (1) gives the parameter estimates of an ACI model without covariates, whereas the estimates reported in column (2) are based on the complete model that captures the characteristics of the limit order arrival process as time-varying covariates. Column (3) reports the estimates for a model specification that ignores the limit order arrival process *during* a spell. In this setting the explanatory variables enter the model, not as time-varying covariates but as marks that are updated at each transaction. The covariates entering the models are defined as in Table II. Note that the cumulated standing ask and bid volumes are standardized by its corresponding seasonality component in order to avoid problems arising by the clear non-stationarity of these variables over a trading day.

Our results show that the inclusion of time-varying covariates does not necessarily improve the econometric specification. Only for the NAB stock is the highest BIC value attained for specification (2). Nevertheless, for all stocks, both models (2) and (3) clearly outperform specification (1), so that the inclusion of covariates leads not only to a better BIC, but also to improved residual diagnostics in all cases. This result illustrates that order book information has substantial explanatory power for the buy and sell pressure in the market.

For all series (with exception of MIM buy transactions), we observe strong persistence in the intensity processes as indicated by the relatively small innovation coefficient estimates and persistence parameter estimates that are close to one. Moreover, we find empirical evidence for significantly positive interdependencies between the two processes. Hence, as a consequence of spill-over effects, an increase of the trading activity on one particular side also increases the intensity on the other market side. Figure 5 shows the empirical autocorrelation function (ACF) and cross-autocorrelation function (CACF) of the estimated buy and sell intensities measured at each transaction time t_i. The ACF is plotted for 300 lags which is on average about 90 minutes for NAB and 80 minutes for BHP. We observe a high serial dependence with respect to the first lags, with a clearly declining autocorrelation function over time. Nevertheless, the buy/sell intensity is highly predictable. For the MIM stock, we observe a significant seasonality pattern which is caused by the lower trading frequency of this stock. For MIM on average 300 lags cover a time span of about 10 trading hours or nearly 2 trading days. The serial dependence in the MIM buy/sell trading intensity is clearly lower than for NAB and BHP, probably caused by the lower liquidity. The cross-autocorrelation plots exhibit contemporaneous correlations of about 0.4 for NAB and BHP and of about 0.2 for MIM. Moreover, the graphs reveal significantly positive cross-autocorrelations between the buy and sell intensity. Thus, clear evidence for spill-over effects between both sides of the market is found.

The Ljung-Box statistics in the Tables IV through VI show that the specifications do capture the dynamics in the data. In nearly all cases, the null hypothesis of no correlation in the ACI residuals cannot be rejected. Furthermore, the parameters of the baseline intensity function indicate a typical pattern of a negative duration dependence, i.e., a decreasing intensity function over time. For the other residual diagnostics, the null hypothesis of no excess dispersion cannot be rejected in most cases, indicating that in each case the model fits the data quite well.

5.1.2 Economic Factors Behind the Buy-Sell Pressure

In order to quantify the influences of these covariates on the buy-sell pressure, we also compute the estimates and the corresponding standard errors of the difference $\gamma^B - \gamma^S$, where γ^B and γ^S denote the coefficients associated with the buy and sell intensity, respectively. Since the intensity is parameterized in log-linear form (see Equations (7) and (8)), the difference between these regression coefficients measures the effect on the log buy-sell ratio $\ln(\lambda^b(t_i; \mathcal{F}_{t_i})/\lambda^s(t_i; \mathcal{F}_{t_i}))$. These estimates are reported in the Tables VII and VIII.

We can summarize the impact of the explanatory variables on the buy/sell intensity and the resulting buy-sell pressure as follows: First, we find clear evidence of positive spill-over effects between consecutive trading days. The differences between closing and opening volumes ($CLOPVOL$) and prices ($CLOPPR$), as well as trading imbalances ($CLBA$) on the preceding day have a significant impact on both the buy and sell intensity during the complete trading day. In particular, a lower trading volume in the opening auction compared to the previous closing auction seems to be a leading indicator for an overall decline of the trading intensity. On the other hand, price movements between closing and opening auction reveal price information which is reflected in a significantly increased (decreased) buy (sell) intensity after upward (downward) price changes. Furthermore, previous imbalances between the total bid and ask volume lead to a significant decrease of the buy intensity, whereas for the sell intensity no clear-cut evidence is found. These findings are confirmed for the net buy pressure, where the excess buy intensity is significantly negatively influenced by the closing to opening price difference and the previous bid-ask volume imbalance.

Second, for both the traded buy and sell volume at the previous transaction ($TRVB$ and $TRVS$), significantly positive coefficients are observed. Thus, the arrival of a large market order increases the overall trading intensity which is consistent with traditional market microstructure theories (see for example Easley and O'Hara, 1987). However, analyzing the impact on the *net* effects reveals slight evidence for buy (sell) trading volumes increasing (decreasing) the buy-sell pressure, which confirms proposition P1. Hence, while the traded quantity increases the general level of the trading frequency, the type of the market order influences the proportion between both market sides.

Third, for the total standing ask and bid volume ($AVOL$ and $BVOL$), no clear-cut effects on either the buy or sell intensity is found. The estimates in the Tables IV through VI provide conflicting results. Unfortunately, this is also confirmed by the estimates of the net effects. For both variables we find positive impacts on the buy-sell pressure in nearly all cases, however, not all are statistically significant. Hence, no convincing evidence in favor of, or against, proposition P2 is found.

Fourth, there is clear evidence of the importance of the buy/sell-specific market depth (ASK_x and BID_x). The steepness of the piecewise slopes measured over the particular volume quantiles have a significant influence on the intensity on both sides of the market, as well as on the resulting buy-sell pressure. At least for the lower quantiles, there is a highly significantly positive (negative) impact of the price impact on the ask (bid) side on the buy intensity. Accordingly, there is a significantly positive (negative) relationship between the sell intensity and the price impact on the bid (ask) side. These results are clearly confirmed by the estimates in Tables VII and VIII, revealing a significant increase (decrease) of the net buy pressure when the price dispersion of the ask (bid) queue rises and thus the steepness of the slope of the ask (bid) reaction curve declines. Hence, these results indicate that the order book queues reflect traders' price setting behavior which in turn reflects their expectations with respect to future price movements. Therefore, positive evidence in favor of the informational value of the limit order book and hence proposition P3 is found. Note that while these effects are highly significant based on the lower volume quantiles of the limit order book, they vanish for higher quantiles. Thus, traders obviously pay particular attention to the lower sections of the order queues which are the relevant ones for most trades. Nevertheless, we clearly reject the notion that market participants mainly focus on the depth revealed by the order queues.

Fifth, as in proposition P4, a large inside spread spread ($SPRD$) significantly decreases both the buy and sell intensity. Thus, in accordance with theoretical market microstructure theory, the tightness of the market is negatively correlated with the overall trading intensity. Moreover, as expected, the bid-ask spread has no significant impact on the net buy pressure. Therefore, proposition P4 is clearly confirmed.

Sixth, past signed midquote changes (DMQ) significantly decrease (increase) the buy (sell) intensity implying significant negative effects on the buy-sell excess intensity which is consistent with proposition P5. These results are caused by the estimates relating to the variable indicating the type of the most recent order ($QASK$).[9]

Seventh, overall the significant interdependencies found between both sides of the market confirm the findings of Ranaldo (2004). Hence, the trading intensity on one particular side of the market is not only driven by the queue and the order arrival on the same side but also by the state of the other side of the market. Moreover, these results indicate that the net buy or sell pressure is particularly strong when the market reveals imbalances between the bid and ask side. These findings also confirm the results of Chordia, Roll, and Subrahmanyam (2002) who illustrate that daily order imbalances are a major source of trading activity and important determinants of market returns. Hence, we show that such effects can not only be identified on an aggregated level but also at the transaction level.

Summarizing the empirical results, we conclude that the state of the limit order book, as well as recent order arrivals have a significant impact on the buy-sell pressure. Our findings clearly reject the hypothesis that traders' preference for immediacy is mainly driven by liquidity arguments. In fact, we provide evidence that the limit order book has informational value. Hence, market participants seem to infer from the current state of the book with respect to information and expected price movements, confirming the findings of Bloomfield, O'Hara, and Saar (2002) and Cao, Hansch, and Wang (2003). Overall, the results are quite stable across all regressions, in particular for the more actively traded NAB and BHP stocks.

[9] The contradictory results implied by model (3) may be caused by the fact that in this specification, the limit order arrival between consecutive transactions is ignored. Then, as the variable $QASK$ indicates the type of the last transaction, it is strongly correlated with the variables $TRVB$ and $TRVS$.

5.2 The Excess Intensity and its Relationship to Price Volatility

Based on the ACI estimates, we construct a measure for the buy-sell pressure, defined as the excess buy intensity evaluated at each observed transaction. In our analysis, we computed the excess intensity in two alternative ways. The most obvious way is to compute the intensity difference

$$\Delta_i := \lambda^B(t_i; \mathcal{F}_{t_i}) - \lambda^S(t_i; \mathcal{F}_{t_i}), \tag{16}$$

where $\lambda^B(\cdot)$ and $\lambda^S(\cdot)$ denote the buy and sell intensity, respectively. We also analyzed the log ratio $\tilde{\Delta}_i := \ln(\lambda^B(t_i; \mathcal{F}_{t_i})/\lambda^S(t_i; \mathcal{F}_{t_i}))$, but as the two measures lead to similar findings, in this paper, we only report the results based on the definition given in Equation (16).

Figure 7 shows the empirical autocorrelation functions of the estimated excess intensity, evaluated at the particular transactions, for all three stocks. These functions display significantly positively autocorrelation with high levels of persistence. In particular, for the more liquid NAB and BHP stocks, the autocorrelation functions display shapes which are typical of long memory processes[10]. Hence, periods of imbalances between the buy and sell side are strongly clustered, and as a consequence, the buy-sell pressure is clearly predictable based on past observations.

An objective of this paper is to explore the influence of the excess intensity Δ_i on the intraday return process. On the one hand, we are interested in the question whether Δ_i predicts trade-to-trade returns. On the other hand, we focus on the relationship between the *absolute* excess intensity $|\Delta_i|$ and the intraday price volatility. Two opposite effects might play an important role: low absolute excess intensities reveal trading periods of balanced trading, indicating that market participants trade on both sides of the market. In this case, trade-to-trade volatility is mainly driven by 'bounce effects' between the two sides of the market. Alternatively, a high absolute excess intensity reflects a strong preference for one particular market side. In this case no bounce effects occur, rather market participants have to account for larger price impacts. Since both effects can obviously lead to substantial price changes, an interesting empirical question is which effect dominates in explaining price change volatility.

In the following, we consider log returns per time that are constructed as in Engle (2000) as the differences between log midquotes standardized by the corresponding trade duration $dt_i := t_i - t_{i-1}$, so that, $r_i = (\ln(mq_i) - \ln(mq_{i-1}))/\sqrt{dt_i}$. In order to account for intraday seasonality effects, we first estimate a cubic spline function for the $|r_i|$ series based on one hour knots and use this to construct a seasonally adjusted series by dividing the original series by the corresponding seasonality components s_i, i.e. $\tilde{r}_i := r_i/s_i$.

For the $\tilde{r}_i$ series, we estimate ARMA-GARCH models[11], in which static regressors are included in both the conditional mean and conditional variance function. Hence, the model is given by

$$\tilde{r}_i = c + a(\tilde{r}_{i-1} - x'_{1,i-1}\gamma_1) + bu_{i-1} + x'_{1,i}\gamma_1 + u_i, \qquad u_i \sim N(0, h_i) \tag{17}$$

$$h_i = \exp\left(\omega + \alpha\frac{|u_{i-1}|}{\sqrt{h_{i-1}}} + \beta(\ln h_{i-1} - x'_{2,i-1}\gamma_2) + x_{2,i}\gamma_2\right), \tag{18}$$

[10]This interesting finding is left for further research.

[11]The lag order is chose according to the BIC.

where $x_{1,i}$ and $x_{2,i}$ denote vectors of regressors included in the conditional mean and variance function respectively, and γ_1 and γ_2 the corresponding coefficient vectors.

Tables IX through XI report the estimated parameters based on a variety of different specifications. In order to provide insights into the explanatory power of particular regressors and to check the stability of the results, we start with simple specifications and subsequently add covariates. In the first group of regressors we include the contemporaneous trade duration dt_i, as well as its lag dt_{i-1} (Panel (1)). The contemporaneous duration has a significantly negative impact on the conditional volatility function, confirming the results of Engle (2000). We also find a significant negative relationship between dt_i and the (signed) return. Hence, upward price movements obviously are associated with a higher trading frequency.

In Panel (2), we include the estimated excess intensity, as well as its absolute value, $\hat{\Delta}_{i-1}$ and $|\hat{\Delta}_{i-1}|$. The increases in the BIC values indicate that these variables have additional explanatory power and improve the overall goodness-of-fit. We find significant influences of the current buy-sell pressure on both the conditional mean and the conditional variance functions. These results show that the buy-sell pressure can predict future returns. Interestingly, we observe significant asymmetries between periods of positive and negative buy-sell pressure. The negative sign of $|\hat{\Delta}_{i-1}|$ indicates that a net sell pressure leads to larger absolute price movements than a net buy pressure. These findings are consistent with the well known result that market participants behave asymmetrically so that "bad news" leads to stronger price responses than good news (see for example Black, 1976 or French, Schwert, and Stambaugh, 1987 among others). Regarding the influence of the absolute buy-sell excess intensity on the trade-to-trade volatility, we find a significantly positive relationship between h_i and $|\hat{\Delta}_{i-1}|$. Thus periods characterized by strong one-sided trading significantly increases the expected volatility. Once again clear asymmetries are observed that exhibit higher volatility in periods of net sell pressure.

In order to control for additional order book effects, we also include the same regressors as used in the intensity regressions (see Panels (3) through (5)). Most regressors are highly significant in nearly all specifications indicating that order book variables clearly predict future returns and volatilities. A detailed analysis of all effects is beyond the scope of this current study and is left for further research. Nevertheless, two main findings can be summarized: Firstly, the sign of each regressor is consistent with our previous findings that traders seem to utilize the current state of the order queues when determining expected price movements. An interesting result is that the slopes of the ask and bid reaction curves ($ASK02$ and $BID02$), as well as the total ask and bid volume ($AVOL$ and $BVOL$) have highly significant influences on the expected return. In particular, expected returns are positive (negative) in periods of low ask (bid) depth, which confirms our results in the previous subsection. Moreover, as expected, our results show that periods of low market depth induce high price impacts leading to a significant increase of the volatility. Secondly, the influence and the explanatory power of the variables $\hat{\Delta}_{i-1}$ and $|\hat{\Delta}_{i-1}|$ remain stable as the extra regressors are included. These results indicate that the buy-sell pressure is an important determinant of the return data generating process and has explanatory power in addition to pure trading or order book characteristics.

6 Conclusions

In this paper, we have studied the relationship between the state of the limit order book and traders' preferences for immediacy on the ask and bid side of the market. This analysis led to a characterization of the determinants of the buy-sell pressure in the market. Using data from three stocks traded at the Australian Stock Exchange (ASX), we exploited detailed limit order information in order to reconstruct the complete limit order book. This allowed the analysis of whether market tightness, the current depth and the standing volume on each side of the market have significant influences on the trading behavior of market participants and thus on the resulting buy-sell pressure.

The simultaneous buy and sell intensity was modelled using a bivariate autoregressive intensity model. The major advantage of this approach is that it permits modelling of the asynchronous arrival of buy and sell orders. Moreover, the intensity approach provides a sensible framework in order to account for the fact that the state of the order book changes whenever a limit order enters the market. This is considered by treating the characteristics associated with the limit order process as time-varying covariates. Our empirical analysis revealed strong cross-autocorrelations, and as a result spill-over effects between both sides of the market. Moreover, the characteristics associated with previous incoming orders, as well as the current state of the order book queues have a significant impact on the buy-sell pressure in the market. An interesting finding was that market participants seem to infer from the order book with respect to expected price movements. In particular, it was shown that traders' preference for immediacy increases when the order queues reveal a higher dispersion of posted limit prices. This result is in contrast with the notion that market agent's trading behavior is dominated by liquidity.

Based on the estimated intensities, a continuous-time measure for the buy-sell pressure in the market was proposed. It was shown that the buy excess intensity (evaluated at each transaction) follows a highly autocorrelated and persistent process. Evidence was provided that the buy-sell pressure in the market is clearly predictable. The findings also illustrated that the buy-sell pressure is an important determinant of trade-to-trade returns and volatility. The excess intensity has significant predictive power for both the conditional mean and the conditional volatility of the intraday return process.

Overall, this study provides deep insights into the questions of how traders learn from order book information and how key variables, such as the time-varying depth, tightness and the standing volume in the queues, influence the trading intensity on both sides of the market, as well as the resulting buy-sell pressure. The fact that traders' preference for immediacy on the buy and sell side is significantly influenced by the state of the order queues indicates that traders learn from the limit order setting and the current demand and supply in the market. These results show that an open limit order book has important informational value and as such is a key factor in providing transparency in a market. Moreover, the possibility of being able to estimate and to predict the time-varying buy-sell pressure in a market opens up a new interesting issue in this field of empirical finance research. In particular, a more detailed analysis of the relationship between the excess intensity and the intraday return process is an important direction for further research. A related interesting research objective concerns the question of whether the persistence in the buy-sell pressure can be systematically exploited for prediction purposes or in designing trading strategies.

References

Al-Suhaibani, M., and L. Kryzanowski (2000): "An Exploratory Analysis of the Order Book, and Order Flow and Execution on the Saudi Stock Market," *Journal of Banking and Finance*, 24, 1323–1357.

Beber, A., and C. Caglio (2003): "Order Submission Strategies and Information: Empirical Evidence from the NYSE," Discussion paper, University of Lausanne, NEWFIN Università Bocconi.

Biais, B., P. Hillion, and C. Spatt (1995): "An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse," *Journal of Finance*, 50, 1655–1689.

Bisière, C., and T. Kamionka (2000): "Timing of Orders, Orders Aggressiveness and the Order Book at the Paris Bourse," *Annales d'Economie et de Statistique*, 60, 43–72.

Black, F. (1976): "Studies in Stock Price Volatility," in *Proceedings of the 1976 Business Meeting of the Business and Economic Statistics Section, American Statistical Association*, pp. 177–181.

Bloomfield, R., M. O'Hara, and G. Saar (2002): "The "Make or Take" Decision in an Electronic Market: Evidence on the Evolution of Liquidity," Discussion paper, Cornell University, New York University.

Blume, L., D. Easley, and M. O'Hara (1994): "Market Statistics and Technical Analysis," *Journal of Finance*, 49 (1), 153–181.

Bowsher, C. G. (2002): "Modelling Security Markets in Continuous Time: Intensity based, Multivariate Point Process Models," Discussion Paper 2002-W22, Nuffield College, Oxford.

Cao, C., O. Hansch, and X. Wang (2003): "The Informational Content of an Open Limit Order Book," Discussion paper, Pennsylvania State University.

Chan, K., and W.-M. Fong (2000): "Trade Size, Order Imbalance, and the Volatility-Volume Relation," *Journal of Financial Economics*, 57, 247–273.

Chordia, T., R. Roll, and A. Subrahmanyam (2002): "Order Imbalance, Liquidity, and Market Returns," *Journal of Financial Economics*, 65, 111–130.

Cohen, K. J., S. F. Maier, R. A. Schwartz, and D. K. Whitcomb (1981): "Transaction Costs, Order Placement Strategy, and Existence of the Bid-Ask Spread," *Journal of Political Economy*, 89(2), 287–305.

Coppejans, M., and I. Domowitz (2002): "An Empirical Analysis of Trades, Orders, and Cancellations in a Limit Order Market," Discussion paper, Duke University.

Cox, D. R., and E. J. Snell (1968): "A General Definition of Residuals," *Journal of the Royal Statistical Society*, B30, 248–265.

Declerck, F. (2000): "Trading Costs on a Limit Order Book Market: Evidence from the Paris Bourse," Discussion paper, Universit de Lille.

Diamond, D. W., and R. E. Verrecchia (1987): "Constraints on Short-Selling and Asset Price Adjustment to Private Information," *Journal of Financial Economics*, 18, 277–311.

Duffie, D., and A. Ziegler (2001): "Liquidation Risk," Discussion paper, Stanford University, University of Lausanne.

Easley, D., and M. O'Hara (1987): "Price, Trade Size, and Information in Securities Markets," *Journal of Financial Economics*, 19, 69–90.

Easley, D., and M. O'Hara (1992): "Time and Process of Security Price Adjustment," *Journal of Finance*, 47 (2), 577–605.

Engle, R. F., and J. R. Russell (1998): "Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction Data," *Econometrica*, 66, 1127–1162.

Engle, R. F. (2000): "The Econometrics of Ultra-High-Frequency Data," *Econometrica*, 68, 1, 1–22.

French, K. R., W. Schwert, and R. F. Stambaugh (1987): "Expected Stock Returns and Volatility," *Journal of Financial Economics*, 19, 3–30.

Glosten, L. R., and P. R. Milgrom (1985): "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders," *Journal of Financial Economics*, 14, 71–100.

Glosten, L. R. (1994): "Is the Electronic Open Limit Order Book Inevitable," *Journal of Finance*, 49, 1127–1161.

Griffiths, M. D., B. F. Smith, D. A. S. Turnbull, and R. W. White (2000): "The Costs and Determinants of Order Aggressiveness," *Journal of Financial Economics*, 56, 65–88.

Handa, P., R. Schwartz, and A. Tiwari (2003): "Quote Setting and Price Formation in an Order Driven Market," *Journal of Financial Markets*, 6, 461–489.

Harris, L., and J. Hasbrouck (1996): "Market vs. Limit Orders: The SuperDOT Evidence on Order Submission Strategy," *Journal of Financial and Quantitative Analysis*, 31(2), 213–231.

Harris, L. (1998): "Optimal Dynamic Order Submission Strategies in Some Stylized Trading Problems," *Financial Markets, Institutions and Instruments*, 7, 1–75.

Hautsch, N. (2004): *Modelling Irregularly Spaced Financial Data – Theory and Practice of Dynamic Duration Models*, vol. 539 of *Lecture Notes in Economics and Mathematical Systems*. Springer, Berlin.

Hawkes, A. G. (1971): "Spectra of Some Self-Exciting and Mutually Exciting Point Processes," *Biometrika*, 58, 83–90.

Hollifield, B., R. A. Miller, P. Sandås, and J. Slive (2002): "Liquidity Supply and Demand in Limit Order Markets," Discussion paper, Centre for Economic Policy Research, London.

Huang, R. D., and H. R. Stoll (1997): "The Components of the Bid/Ask-Spread: A General Approach," *The Review of Financial Studies*, 10, 995–1034.

Kyle, A. S. (1985): "Continuous Auctions and Insider Trading," *Econometrica*, 53 (6), 1315–1335.

Lee, Y.-T., Y.-J. Liu, R. Roll, and A. Subrahmanyam (2003): "Order Imbalances and Market Efficiency: Evidence from the Taiwan Stock Exchange," Discussion paper, National Chengchi University, Anderson School of Management.

Linnainmaa, J. (2003): "Who Makes the Limit Order Book? Implications on Contrarian Strategies and the Disposition Effect," Discussion paper, Helsinki School of Economics.

Lo, I., and S. G. Sapp (2003): "Order Submission: The Choice between Limit and Market Orders," Discussion paper, University of Waikato, University of Western Ontario.

McCulloch, J. (2003): "True Spreads and Optimal Tick Size on the Australian Stock Exchange," Ph.D. thesis, University of Technology, Sydney.

Niemeyer, J., and P. Sandås (1995): "An Empirical Analysis of the Trading Structure at the Stockholm Stock Exchange," Discussion paper, Stockholm School of Economics.

Ranaldo, A. (2004): "Order Aggressiveness in Limit Order Book Markets," *Journal of Financial Markets*, 7, 53–74.

Russell, J. R. (1999): "Econometric Modeling of Multivariate Irregularly-Spaced High-Frequency Data," Discussion paper, University of Chicago.

Seppi, D. J. (1997): "Liquidity Provision with Limit Orders and Strategic Specialist," *Review of Financial Studies*, 1(1), 103–150.

Stoll, H. (1989): "Inferring the Components of the Bid/Ask Spread: Theory and Empirical Tests," *Journal of Finance*, 44, 115–134.

Wang, J. (1999): "Asymmetric Information and the Bid-Ask Spread: An Empirical Comparison Between Automated Order Execution and Open Outcry Auction," *Journal of International Financial Markets, Institutions and Money*, 9(2), 115–128.

Winne, R. D., and C. D'Hondt (2003): "Rebuilding the Limit Order Book on Euronext or How to Improve Market Liquidity Assessment," Discussion paper, Catholic University of Mons.

Zovko, I., and J. D. Farmer (2002): "The Power of Patience: A Behavioral Regularity in Limit Order Placement," Discussion paper, Santa Fee Institute, University of Amsterdam.

Appendix

A Tables

Table I
Market Schedule of the ASX.

This table gives an overview of the market phases over a trading day at the Australian Stock Exchange (ASX).

Market Phase	Time	Functionality
Market Enquiry	(approx) 3:00 - 7:00	Enquiry on current orders only.
Market Pre-Open	7:00 - 10:00	Can enter, delete and amend orders and enter off-market trades.
Market Opening	10:00 - 10:09	Staggered call auctions open continuous trading.
Normal Market	10:09 - 16:00	Can enter, amend and delete orders. Overlapping buy and sell orders execute immediately.
Closing Call Auction	16:05($\pm$ 15 seconds random)	Can enter, delete and amend orders prior to the closing call auction.
Late Trading	16:05 - 17:00	Can enter, delete and amend orders. Late trades permitted with restrictions.
Market Closed	17:00 - 19:00	Can only delete orders.

Table II
Explanatory Variables.

This table provides the definition of the explanatory variables used in the empirical study.

	Variables that are constant during a trading day
$CLVOL(-1)$	Closing volume at previous day
$CLPR(-1)$	Closing price at previous day
$BIDVOL(-1)$	Total bid volume at the previous closing of the normal market
$ASKVOL(-1)$	Total ask volume at the previous closing of the normal market
$OPVOL$	Current opening volume
$OPPR$	Current opening price
$CLOPVOL$	$\ln(CLVOL(-1)) - \ln(OPVOL)$
$CLOPPR$	$\ln(CLPR(-1)) - \ln(OPPR)$
$CLBA$	$\ln(BIDVOL(-1)) - \ln(ASKVOL(-1))$
	Variables observed at each transaction
BUY	1: if the trade is a buy, 0: otherwise
TRV	logarithm of traded volume
$TRVB$	logarithm of traded buy volume
$TRVS$	logarithm of traded sell volume
	Variables observed at each arriving order
$AVOL$	seasonally adjusted total volume on the ask queue
$BVOL$	seasonally adjusted total volume on the bid queue
A_x	price associated with the x% quantile of the cumulated volume on the ask queue
B_x	price associated with the x% quantile of the cumulated volume on the bid queue
MQ	$(A_0 + B_0)/2$
$ASK02$	$(A_{02} - MQ)/MQ * 100$
$ASK05$	$(A_{05} - A_{02})/MQ * 100$
$ASK10$	$(A_{10} - A_{05})/MQ * 100$
$ASK50$	$(A_{50} - A_{10})/MQ$
$ASK90$	$(A_{90} - A_{50})/MQ$
$BID02$	$(MQ - B_{02})/MQ * 100$
$BID05$	$(B_{02} - B_{05})/MQ * 100$
$BID10$	$(B_{05} - B_{10})/MQ * 100$
$BID50$	$(B_{10} - B_{50})/MQ$
$BID90$	$(B_{50} - B_{90})/MQ$
$SPRD$	bid-ask spread
DMQ	$DMQ = MQ_i - MQ_{i-1}$
$QASK$	1: if an order is an ask, 0: if an order is a bid

Table III
Descriptive Statistics of Trade and Limit Order Arrival Processes at the ASX

This table gives descriptive statistics and Ljung-Box statistics associated with the trade and limit order arrival process of the NAB, BHP and MIM stocks. The data are extracted from ASX trading and the sample period is all trading days of July 2002. Duration statistics measured in seconds. Overnight spells are ignored.

	NAB	BHP	MIM
Number of trades	24715	29591	3839
Number of buys	13510	18155	1762
Number of sells	11205	11436	2077
Number of limit orders (incl. changes and cancellations)	34093	44302	8707
Number of ask orders	9462	11907	2690
Number of bid orders	11378	11907	2872
Number of ask changes	3402	4221	683
Number of bid changes	3607	4615	585
Number of ask cancellations	3000	3757	770
Number of bid cancellations	3244	3785	1107
Trade durations			
Mean	19.704	16.771	121.610
Standard deviation	36.085	30.257	190.295
LB(20) statistic	9052	10465	970
Buy durations			
Mean	36.014	27.320	262.701
Standard deviations	65.709	46.253	507.781
LB(20) statistic	5878	7051	268
Sell durations			
Mean	44.023	43.948	224.947
Standard deviation	75.660	79.373	358.417
LB(20) statistic	4024	5105	342
Limit order durations (excl. changes and cancellations)			
Mean	23.362	17.774	84.058
Standard deviation	40.619	30.884	124.858
LB(20) statistic	8724	9338	2051
Ask order durations (excl. changes and cancellations)			
Mean	51.383	41.629	172.397
Standard deviation	83.433	68.776	244.677
LB(20) statistic	4210	5460	984
Bid order durations (excl. changes and cancellations)			
Mean	42.760	30.944	162.380
Standard deviation	68.575	50.165	247.976
LB(20) statistic	5505	6890	666

Table IV
Estimates of ACI models for the Buy and Sell Arrival Processes of the NAB stock

This table gives the maximum likelihood estimates of a bivariate ACI(1,1) model for the buy-specific (B) and sell-specific (S) conditional intensity processes given the information set $\mathcal{F}_t$ at (calendar) time t

$$\lambda^k(t;\mathcal{F}_t) = \lim_{\Delta \downarrow 0} \frac{1}{\Delta} \Pr\left[(N^k(t+\Delta) - N^k(t)) > 0 \,|\mathcal{F}_t \right], \quad k \in \{B, S\},$$

where $N^k(t) = \sum_{i \geq 1} \mathbb{1}_{\{t_i^k \leq t\}}$ counts all process-specific points t_i^k with $t_i^k \leq t$. The intensity processes are modelled as

$$\begin{aligned} & \lambda^k(t;\mathcal{F}_t) = \Psi^k(t)\lambda_0^k(t)s^k(t), \; k \in \{B,S\}, \\ \text{where} \qquad & \Psi^k(t) = \exp\left(\tilde{\Psi}^k_{M(t)+1} + z'_{M(t)}\gamma^k + z^{0\prime}_{M^0(t)}\tilde{\gamma}^k \right), \\ & \lambda_0^k(t) = \exp(\omega^k) \prod_{r \in \{B,S\}} \frac{x^r(t)^{p_r^k - 1}}{1 + \kappa_r^k x^r(t)^{p_r^k}}, \; (p_r^k > 0, \; \kappa_r^k \geq 0) \end{aligned}$$

and $s^k(t)$ denotes a spline function which is specified based on one hour knots. γ^k and $\tilde{\gamma}^k$ respectively, are the coefficient vectors associated with marks z_i observed at each event of the pooled process $\{t_i\}_{i=1}^n$ and time-varying covariates z_i^0 observed at points $\{t_i^0\}_{i=1}^{n^0}$. Moreover, $M^x(t) = \sum_{i \geq 1} \mathbb{1}_{\{t_i^x < t\}}$ with $x \in \{0, B, S\}$ and $M(t) = \sum_{i \geq 1} \mathbb{1}_{\{t_i < t\}}$ denote the right-continuous counting functions associated with the processes $\{t_i^x\}$ and $\{t_i\}$, respectively. $x^k(t) = t - t^k_{M^k(t)}$ corresponds to the backward recurrence time until the most recent point. The vector $\tilde{\Psi}'_i = \left(\tilde{\Psi}_i^B, \tilde{\Psi}_i^S \right)$ is specified by $\tilde{\Psi}_i = \left(A^k \breve{\epsilon}_{i-1} + B\tilde{\Psi}_{i-1} \right) y^k_{i-1}$ with $A^k = \{\alpha_j^k\}$ denoting a (2×1) vector, $B = \{\beta_{ij}\}$ a (2×2) matrix and y_i^k defining an indicator variable that takes the value 1 if the i-th point of the pooled process is of type k. The innovation $\breve{\epsilon}_i$ is given by $\breve{\epsilon}_i := \left(1 - \int_{t^k_{i-1}}^{t^k_i} \lambda^k(u;\mathcal{F}_u)du \right) y_i^k$.

The sample contains all market and limit orders (excl. changes and cancellations) of the NAB stock during July 2002. Standard errors are computed based on OPG estimates. The time series are re-initialized at each trading day.

Panel (1): No covariates included. Panel (2): Covariates change whenever a new order arrives in the market. Panel (3): Covariates change only whenever a transaction is executed.

	(1)		(2)		(3)	
Obs (n)	24715		24715		24715	
Obs (n^0)	58808		58808		58808	
LL	-36963		-35271		-35571	
BIC	-37085		-35594		-35894	
	est.	S.E.	est.	S.E.	est.	S.E.
			ACI parameters buy trades			
ω^B	0.106	0.048	-0.731	0.197	-0.790	0.150
p_B^B	0.934	0.010	0.894	0.010	0.928	0.010
p_B^S	0.892	0.008	0.969	0.010	0.923	0.010
κ_B^B	0.089	0.010	0.079	0.011	0.069	0.010
κ_B^S	-0.002	0.004	0.010	0.004	0.005	0.005
α_B^B	0.028	0.002	0.072	0.005	0.081	0.006
α_B^S	0.006	0.002	0.030	0.005	0.039	0.006
β_B^B	0.996	0.002	0.966	0.015	0.916	0.021
β_B^S	0.996	0.003	0.911	0.021	0.870	0.029
			ACI parameters sell trades			
ω^S	-0.064	0.047	0.123	0.177	0.017	0.117
p_S^B	0.869	0.008	0.939	0.010	0.889	0.010
p_S^S	0.966	0.012	0.907	0.013	0.959	0.012
κ_S^B	-0.013	0.003	0.000	0.004	-0.008	0.003
κ_S^S	0.105	0.011	0.078	0.011	0.080	0.010
α_S^B	0.011	0.003	0.024	0.005	0.024	0.005
α_S^S	0.052	0.004	0.070	0.006	0.071	0.006
β_S^B	0.982	0.010	0.973	0.015	0.958	0.018
β_S^S	0.977	0.011	0.932	0.019	0.930	0.021
			Seasonality parameters			
$s_{11:00}$	-1.043	0.115	-1.332	0.089	-1.366	0.082
$s_{12:00}$	0.858	0.196	1.102	0.161	1.206	0.146
$s_{13:00}$	-0.686	0.153	-0.421	0.129	-0.557	0.117
$s_{14:00}$	1.489	0.139	1.132	0.123	1.230	0.113
$s_{15:00}$	0.024	0.146	-0.036	0.126	-0.060	0.113
$s_{16:00}$	0.138	0.222	0.080	0.163	0.121	0.148

Table IV continued

Diagnostics: Log Likelihood (LL), Bayes Information Criterion (BIC) and diagnostics (mean, standard deviation, Ljung-Box statistics and excess dispersion test) of ACI residuals $\hat{\varepsilon}_i^s$.

	est.	S.E.	est.	S.E.	est.	S.E.
Static covariates buy trades						
$CLOPVOL$			-0.021	0.013	-0.027	0.011
$CLOPPR$			-6.104	1.848	-6.083	1.573
$CLBAL$			-0.076	0.047	-0.100	0.040
$TRVB$			0.026	0.005	0.042	0.005
$TRVS$			0.024	0.005	0.006	0.005
Static covariates sell trades						
$CLOPVOL$			-0.044	0.015	-0.046	0.013
$CLOPPR$			5.521	2.054	5.476	1.873
$CLBAL$			-0.096	0.053	-0.094	0.049
$TRVB$			0.044	0.006	0.025	0.006
$TRVS$			0.051	0.006	0.072	0.005
Time-varying covariates buy trades						
$AVOL^B$			0.444	0.113	0.335	0.094
$BVOL^B$			0.135	0.056	0.144	0.046
$ASK02^B$			0.379	0.110	0.376	0.102
$BID02^B$			-1.075	0.173	-0.909	0.163
$ASK05^B$			0.210	0.070	0.238	0.070
$BID05^B$			-0.440	0.137	-0.341	0.132
$ASK10^B$			0.083	0.044	0.097	0.042
$BID10^B$			0.033	0.087	-0.007	0.087
$ASK50^B$			6.248	1.286	6.224	1.044
$BID50^B$			3.704	1.849	3.666	1.598
$ASK90^B$			7.272	0.874	7.170	0.761
$BID90^B$			0.959	1.012	0.910	0.918
$SPRD^B$			-0.248	0.008	-0.145	0.007
DMQ^B			-0.270	0.009	-0.216	0.006
$QASK^B$			0.041	0.018	-0.045	0.019
Time-varying covariates sell trades						
$AVOL^S$			-0.097	0.113	-0.112	0.094
$BVOL^S$			0.055	0.057	0.022	0.048
$ASK02^S$			-0.518	0.127	-0.419	0.117
$BID02^S$			-0.640	0.189	-0.314	0.179
$ASK05^S$			-0.143	0.079	-0.091	0.076
$BID05^S$			0.591	0.144	0.441	0.126
$ASK10^S$			-0.025	0.047	0.013	0.045
$BID10^S$			0.250	0.095	0.278	0.091
$ASK50^S$			-1.466	1.355	-1.598	1.178
$BID50^S$			2.740	1.944	2.761	1.805
$ASK90^S$			3.424	0.965	3.478	0.906
$BID90^S$			-0.175	1.055	-0.212	1.019
$SPRD^S$			-0.210	0.008	-0.141	0.007
DMQ^S			0.357	0.010	0.273	0.008
$QASK^S$			-0.044	0.020	-0.017	0.020

	stat.	p-value	stat.	p-value	stat.	p-value
Diagnostics of ACI residuals for the buy series						
Mean of $\hat{\varepsilon}_i$	1.003		1.000		1.000	
S.D. of $\hat{\varepsilon}_i$	1.005		0.998		1.018	
LB(20) of $\hat{\varepsilon}_i$	49.041	0.000	34.867	0.020	59.034	0.000
Exc. disp.	0.482	0.6296	0.132	0.894	1.546	0.121
Diagnostics of ACI residuals for the sell series						
Mean of $\hat{\varepsilon}_i$	1.001		1.000		1.000	
S.D. of $\hat{\varepsilon}_i$	1.000		1.001		1.020	
LB(20) of $\hat{\varepsilon}_i$	34.292	0.024	19.158	0.511	21.761	0.353
Exc. disp.	0.037	0.970	0.119	0.905	1.577	0.114

Table V
Estimates of ACI models for the Buy and Sell Arrival Processes of the BHP stock

This table gives the maximum likelihood estimates of a bivariate ACI(1,1) model for the buy-specific (B) and sell-specific (S) conditional intensity processes given the information set $\mathcal{F}_t$ at (calendar) time t

$$\lambda^k(t;\mathcal{F}_t) = \lim_{\Delta \downarrow 0} \frac{1}{\Delta} \Pr\left[(N^k(t+\Delta) - N^k(t)) > 0 \,|\mathcal{F}_t \right], \quad k \in \{B, S\},$$

where $N^k(t) = \sum_{i \geq 1} \mathbf{1}_{\{t_i^k \leq t\}}$ counts all process-specific points t_i^k with $t_i^k \leq t$. The intensity processes are modelled as

$$\begin{aligned} \lambda^k(t;\mathcal{F}_t) &= \Psi^k(t)\lambda_0^k(t)s^k(t), \; k \in \{B, S\}, \\ \text{where} \qquad \Psi^k(t) &= \exp\left(\tilde{\Psi}^k_{M(t)+1} + z'_{M(t)}\gamma^k + z^{0\prime}_{M^0(t)}\tilde{\gamma}^k \right), \\ \lambda_0^k(t) &= \exp(\omega^k) \prod_{r \in \{B,S\}} \frac{x^r(t)^{p_r^k - 1}}{1 + \kappa_r^k x^r(t)^{p_r^k}}, \; (p_r^k > 0, \; \kappa_r^k \geq 0) \end{aligned}$$

and $s^k(t)$ denotes a spline function which is specified based on one hour knots. γ^k and $\tilde{\gamma}^k$ respectively, are the coefficient vectors associated with marks z_i observed at each event of the pooled process $\{t_i\}_{i=1}^n$ and time-varying covariates z_i^0 observed at points $\{t_i^0\}_{i=1}^{n^0}$. Moreover, $M^x(t) = \sum_{i \geq 1} \mathbf{1}_{\{t_i^x < t\}}$ with $x \in \{0, B, S\}$ and $M(t) = \sum_{i \geq 1} \mathbf{1}_{\{t_i < t\}}$ denote the right-continuous counting functions associated with the processes $\{t_i^x\}$ and $\{t_i\}$, respectively. $x^k(t) = t - t^k_{M^k(t)}$ corresponds to the backward recurrence time until the most recent point. The vector $\tilde{\Psi}'_i = \left(\tilde{\Psi}_i^B, \tilde{\Psi}_i^S \right)$ is specified by $\tilde{\Psi}_i = \left(A^k \breve{\epsilon}_{i-1} + B\tilde{\Psi}_{i-1} \right) y_{i-1}^k$ with $A^k = \{\alpha_j^k\}$ denoting a (2×1) vector, $B = \{\beta_{ij}\}$ a (2×2) matrix and y_i^k defining an indicator variable that takes the value 1 if the i-th point of the pooled process is of type k. The innovation $\breve{\epsilon}_i$ is given by $\breve{\epsilon}_i := \left(1 - \int_{t_{i-1}^k}^{t_i^k} \lambda^k(u;\mathcal{F}_u)du \right) y_i^k$.

The sample contains all market and limit orders (excl. changes and cancellations) of the BHP stock during July 2002. Standard errors are computed based on OPG estimates. The time series are re-initialized at each trading day.

Panel (1): No covariates included. Panel (2): Covariates change whenever a new order arrives in the market. Panel (3): Covariates change only whenever a transaction is executed.

	(1)		(2)		(3)	
Obs (n)	29591		29591		29591	
Obs (n^0)	73893		73893		73893	
LL	-43511		-41786		-41524	
BIC	-43635		-42115		-41854	
	est.	S.E.	est.	S.E.	est.	S.E.
ACI parameters buy trades						
ω^B	0.388	0.045	0.311	0.113	0.282	0.077
p_B^B	0.913	0.007	0.899	0.007	0.927	0.008
p_B^S	0.933	0.006	0.979	0.008	0.942	0.008
κ_B^B	0.062	0.007	0.048	0.007	0.049	0.007
κ_B^S	-0.004	0.002	0.001	0.002	-0.000	0.002
α_B^B	0.046	0.002	0.053	0.003	0.051	0.003
α_B^S	0.015	0.003	0.011	0.003	0.015	0.003
β_B^B	0.990	0.003	0.981	0.005	0.979	0.005
β_B^S	0.990	0.005	0.988	0.006	0.986	0.007
ACI parameters sell trades						
ω^S	0.035	0.046	0.240	0.133	-0.016	0.106
p_S^B	0.948	0.009	1.012	0.010	0.962	0.011
p_S^S	0.909	0.010	0.875	0.011	0.912	0.011
κ_S^B	0.010	0.006	0.041	0.007	0.046	0.009
κ_S^S	0.080	0.009	0.050	0.008	0.041	0.007
α_S^B	0.024	0.003	0.020	0.004	0.028	0.004
α_S^S	0.083	0.005	0.092	0.005	0.095	0.006
β_S^B	0.970	0.007	0.962	0.009	0.919	0.012
β_S^S	0.983	0.009	0.965	0.011	0.978	0.013
Seasonality parameters						
$s_{11:00}$	-1.458	0.098	-1.306	0.104	-1.265	0.099
$s_{12:00}$	1.311	0.181	1.078	0.188	1.023	0.178
$s_{13:00}$	-0.455	0.148	-0.399	0.148	-0.410	0.139
$s_{14:00}$	1.024	0.125	1.111	0.134	1.156	0.129
$s_{15:00}$	-0.026	0.148	-0.130	0.152	-0.133	0.144
$s_{16:00}$	0.380	0.219	0.426	0.203	0.449	0.194

Table V continued

Diagnostics: Log Likelihood (LL), Bayes Information Criterion (BIC) and diagnostics (mean, standard deviation, Ljung-Box statistics and excess dispersion test) of ACI residuals $\hat{\varepsilon}_i^s$.

	est.	S.E.	est.	S.E.	est.	S.E.
			Static covariates buy trades			
$CLOPVOL$			0.011	0.045	-0.041	0.040
$CLOPPR$			-5.559	1.558	-5.530	1.376
$CLBAL$			-0.124	0.053	-0.149	0.047
$TRVB$			0.037	0.004	0.050	0.004
$TRVS$			0.028	0.004	0.012	0.004
			Static covariates sell trades			
$CLOPVOL$			-0.189	0.040	-0.165	0.034
$CLOPPR$			-1.668	1.335	-1.695	1.092
$CLBAL$			0.065	0.047	0.057	0.038
$TRVB$			0.050	0.006	0.024	0.005
$TRVS$			0.059	0.005	0.071	0.005
			Time-varying covariates buy trades			
$AVOL^B$			0.478	0.115	0.273	0.107
$BVOL^B$			-0.002	0.065	0.014	0.058
$ASK02^B$			1.493	0.075	1.130	0.071
$BID02^B$			-2.103	0.118	-1.526	0.111
$ASK05^B$			0.195	0.058	0.192	0.055
$BID05^B$			-0.190	0.079	-0.188	0.075
$ASK10^B$			0.111	0.037	0.109	0.034
$BID10^B$			-0.110	0.053	-0.093	0.048
$ASK50^B$			-1.245	1.007	-1.257	0.853
$BID50^B$			-3.655	1.850	-3.665	1.715
$ASK90^B$			-2.215	0.910	-2.187	0.823
$BID90^B$			0.335	2.039	0.340	1.887
$SPRD^B$			-0.432	0.029	-0.231	0.022
DMQ^B			-0.581	0.022	-0.531	0.016
$QASK^B$			0.076	0.016	-0.003	0.016
			Time-varying covariates sell trades			
$AVOL^S$			0.078	0.107	0.124	0.093
$BVOL^S$			-0.217	0.058	-0.214	0.049
$ASK02^S$			-1.691	0.110	-1.093	0.106
$BID02^S$			1.818	0.065	1.378	0.093
$ASK05^S$			-0.110	0.072	-0.051	0.066
$BID05^S$			0.432	0.085	0.342	0.079
$ASK10^S$			0.109	0.045	0.089	0.042
$BID10^S$			0.066	0.055	0.146	0.051
$ASK50^S$			-0.204	0.974	-0.279	0.807
$BID50^S$			5.952	1.784	5.943	1.469
$ASK90^S$			-1.602	0.951	-1.625	0.786
$BID90^S$			0.868	2.218	0.852	1.785
$SPRD^S$			-0.466	0.032	-0.325	0.022
DMQ^S			0.770	0.023	0.661	0.016
$QASK^S$			-0.027	0.020	0.053	0.020
			Diagnostics of ACI residuals for the buy series			
	stat.	p-value	stat.	p-value	stat.	p-value
Mean of $\hat{\varepsilon}_i$	1.003		1.003		1.002	
S.D. of $\hat{\varepsilon}_i$	1.005		1.002		1.020	
LB(20) of $\hat{\varepsilon}_i$	54.709	0.000	43.331	0.001	38.484	0.007
Exc. disp.	0.514	0.607	0.236	0.813	1.954	0.050
			Diagnostics of ACI residuals for the sell series			
	stat.	p-value	stat.	p-value	stat.	p-value
Mean of $\hat{\varepsilon}_i$	1.005		1.004		1.003	
S.D. of $\hat{\varepsilon}_i$	1.010		1.010		1.031	
LB(20) of $\hat{\varepsilon}_i$	30.063	0.068	30.580	0.061	20.012	0.457
Exc. disp.	0.785	0.432	0.775	0.438	2.450	0.014

Table VI
Estimates of ACI models for the Buy and Sell Arrival Processes of the MIM stock

This table gives the maximum likelihood estimates of a bivariate ACI(1,1) model for the buy-specific (B) and sell-specific (S) conditional intensity processes given the information set $\mathcal{F}_t$ at (calendar) time t

$$\lambda^k(t;\mathcal{F}_t) = \lim_{\Delta \downarrow 0} \frac{1}{\Delta} \Pr\left[(N^k(t+\Delta) - N^k(t)) > 0 \,|\mathcal{F}_t \right], \quad k \in \{B,S\},$$

where $N^k(t) = \sum_{i \geq 1} \mathbf{1}_{\{t_i^k \leq t\}}$ counts all process-specific points t_i^k with $t_i^k \leq t$. The intensity processes are modelled as

$$\lambda^k(t;\mathcal{F}_t) = \Psi^k(t)\lambda_0^k(t)s^k(t), \; k \in \{B,S\},$$

$$\text{where} \qquad \Psi^k(t) = \exp\left(\tilde{\Psi}^k_{M(t)+1} + z'_{M(t)}\gamma^k + z^{0\prime}_{M^0(t)}\tilde{\gamma}^k \right),$$

$$\lambda_0^k(t) = \exp(\omega^k) \prod_{r \in \{B,S\}} \frac{x^r(t)^{p_r^k - 1}}{1 + \kappa_r^k x^r(t)^{p_r^k}}, \; (p_r^k > 0, \; \kappa_r^k \geq 0)$$

and $s^k(t)$ denotes a spline function which is specified based on one hour knots. γ^k and $\tilde{\gamma}^k$ respectively, are the coefficient vectors associated with marks z_i observed at each event of the pooled process $\{t_i\}_{i=1}^n$ and time-varying covariates z_i^0 observed at points $\{t_i^0\}_{i=1}^{n^0}$. Moreover, $M^x(t) = \sum_{i \geq 1} \mathbf{1}_{\{t_i^x < t\}}$ with $x \in \{0, B, S\}$ and $M(t) = \sum_{i \geq 1} \mathbf{1}_{\{t_i < t\}}$ denote the right-continuous counting functions associated with the processes $\{t_i^x\}$ and $\{t_i\}$, respectively. $x^k(t) = t - t^k_{M^k(t)}$ corresponds to the backward recurrence time until the most recent point. The vector $\tilde{\Psi}'_i = \left(\tilde{\Psi}_i^B, \tilde{\Psi}_i^S \right)$ is specified by $\tilde{\Psi}_i = \left(A^k \breve{\epsilon}_{i-1} + B\tilde{\Psi}_{i-1} \right) y^k_{i-1}$ with $A^k = \{\alpha_j^k\}$ denoting a (2×1) vector, $B = \{\beta_{ij}\}$ a (2×2) matrix and y_i^k defining an indicator variable that takes the value 1 if the i-th point of the pooled process is of type k. The innovation $\breve{\epsilon}_i$ is given by $\breve{\epsilon}_i := \left(1 - \int_{t^k_{i-1}}^{t_i^k} \lambda^k(u;\mathcal{F}_u)du \right) y_i^k$.

The sample contains all market and limit orders (excl. changes and cancellations) of the MIM stock during July 2002. Standard errors are computed based on OPG estimates. The time series are re-initialized at each trading day.
Panel (1): No covariates included. Panel (2): Covariates change whenever a new order arrives in the market. Panel (3): Covariates change only whenever a transaction is executed.

	(1)		(2)		(3)	
Obs (n)	3839		3839		3839	
Obs (n^0)	12546		12546		12546	
LL	-5490		-5118		-5140	
BIC	-5589		-5382		-5404	
	est.	S.E.	est.	S.E.	est.	S.E.
			ACI parameters buy trades			
ω^B	-0.215	0.089	-0.868	0.422	-1.280	0.291
p_B^B	0.753	0.024	0.800	0.023	0.802	0.023
p_B^S	0.977	0.022	0.924	0.027	0.907	0.027
κ_B^B	0.100	0.035	0.024	0.021	0.028	0.022
κ_B^S	-0.016	0.007	-0.011	0.011	-0.013	0.011
α_B^B	0.269	0.029	0.205	0.022	0.246	0.028
α_B^S	-0.080	0.028	-0.102	0.025	-0.070	0.028
β_B^B	0.823	0.057	0.932	0.044	0.850	0.058
β_B^S	0.461	0.114	0.568	0.091	0.358	0.115
			ACI parameters sell trades			
ω^S	-0.143	0.083	-0.696	0.290	-0.105	0.154
p_S^B	1.018	0.020	0.995	0.025	0.973	0.025
p_S^S	0.779	0.022	0.813	0.022	0.802	0.021
κ_S^B	-0.001	0.004	-0.004	0.005	-0.001	0.006
κ_S^S	0.027	0.027	-0.002	0.021	-0.023	0.018
α_S^B	0.001	0.018	-0.026	0.017	-0.017	0.015
α_S^S	0.121	0.018	0.119	0.013	0.088	0.011
β_S^B	0.909	0.046	0.874	0.042	0.901	0.031
β_S^S	0.913	0.037	0.967	0.020	0.991	0.014
			Seasonality parameters			
$s_{11:00}$	-0.833	0.204	-1.011	0.210	-0.787	0.271
$s_{12:00}$	0.434	0.370	0.900	0.360	0.549	0.429
$s_{13:00}$	-0.335	0.306	-0.795	0.306	-0.675	0.326
$s_{14:00}$	1.365	0.289	1.632	0.295	1.745	0.334
$s_{15:00}$	-0.437	0.320	-0.477	0.317	-0.528	0.354
$s_{16:00}$	1.701	0.445	1.671	0.428	1.744	0.515

Table VI continued

Diagnostics: Log Likelihood (LL), Bayes Information Criterion (BIC) and diagnostics (mean, standard deviation, Ljung-Box statistics and excess dispersion test) of ACI residuals $\hat{\varepsilon}_i^s$.

	est.	S.E.	est.	S.E.	est.	S.E.
Static covariates buy trades						
$CLOPVOL$			-0.075	0.035	-0.051	0.032
$CLOPPR$			-2.967	3.594	-0.928	3.481
$CLBAL$			-0.280	0.122	-0.329	0.112
$TRVB$			0.072	0.014	0.077	0.015
$TRVS$			0.037	0.015	0.028	0.016
Static covariates sell trades						
$CLOPVOL$			0.064	0.038	0.011	0.037
$CLOPPR$			14.201	4.244	13.242	3.976
$CLBAL$			0.182	0.131	0.116	0.128
$TRVB$			0.049	0.014	0.040	0.014
$TRVS$			0.065	0.014	0.060	0.013
Time-varying covariates buy trades						
$AVOL^B$			-0.029	0.325	0.249	0.296
$BVOL^B$			0.224	0.171	0.383	0.144
$ASK02^B$			0.850	0.083	0.662	0.090
$BID02^B$			-1.288	0.216	-0.984	0.183
$ASK05^B$			0.339	0.078	0.282	0.083
$BID05^B$			-0.858	0.144	-0.584	0.144
$ASK10^B$			0.184	0.061	0.139	0.061
$BID10^B$			-0.529	0.092	-0.301	0.097
$ASK50^B$			-1.414	2.184	-2.087	2.042
$BID50^B$			1.413	3.376	4.855	2.991
$ASK90^B$			3.889	3.780	0.820	3.771
$BID90^B$			-1.674	1.833	-2.309	1.636
$SPRD^B$			-0.219	0.231	-0.186	0.184
DMQ^B			-0.698	0.151	-0.637	0.090
$QASK^B$			0.050	0.051	-0.000	0.060
Time-varying covariates sell trades						
$AVOL^S$			0.261	0.329	-0.398	0.327
$BVOL^S$			0.191	0.175	-0.102	0.167
$ASK02^S$			-0.576	0.122	-0.543	0.108
$BID02^S$			1.112	0.091	0.735	0.083
$ASK05^S$			-0.183	0.075	-0.174	0.071
$BID05^S$			0.646	0.077	0.541	0.078
$ASK10^S$			0.056	0.061	0.027	0.057
$BID10^S$			0.430	0.068	0.375	0.066
$ASK50^S$			-0.844	2.441	-0.246	2.437
$BID50^S$			6.595	3.270	4.729	3.153
$ASK90^S$			-2.261	4.042	-1.816	4.025
$BID90^S$			-4.540	1.763	-4.698	1.742
$SPRD^S$			-0.346	0.165	0.030	0.134
DMQ^S			0.712	0.129	0.514	0.075
$QASK^S$			0.011	0.045	0.169	0.048
Diagnostics of ACI residuals for the buy series						
	stat.	S.E.	stat.	S.E.	stat.	S.E.
Mean of $\hat{\varepsilon}_i$	0.980		0.989		0.988	
S.D. of $\hat{\varepsilon}_i$	0.985		1.019		1.006	
LB(20) of $\hat{\varepsilon}_i$	21.608	0.362	20.120	0.450	24.263	0.231
Exc. disp.	0.427	0.6691	0.593	0.553	0.178	0.858
Diagnostics of ACI residuals for the sell series						
	stat.	p-value	stat.	p-value	stat.	p-value
Mean of $\hat{\varepsilon}_i$	0.994		1.001		1.004	
S.D. of $\hat{\varepsilon}_i$	1.014		1.039		1.042	
LB(20) of $\hat{\varepsilon}_i$	18.340	0.565	14.533	0.802	10.737	0.952
Exc. disp.	0.484	0.627	1.284	0.199	1.392	0.163

Table VII
Estimates of the Buy-Sell Pressure based on ACI specification (2)

This table gives the estimates of the difference $\gamma^B - \gamma^S$. The estimates and corresponding standard errors are computed based on the estimates of ACI specification (2) reported in the Tables IV through VI.

	NAB		BHP		MIM	
	est.	S.E.	est.	S.E.	est.	S.E.
$CLOPVOL$	0.018	0.015	0.123	0.045	-0.063	0.050
$CLOPPR$	-11.559	2.139	-3.835	1.479	-14.170	5.524
$CLBAL$	-0.006	0.055	-0.207	0.052	-0.446	0.177
$TRVB$	0.016	0.007	0.025	0.007	0.037	0.020
$TRVS$	-0.066	0.007	-0.058	0.007	-0.032	0.020
$AVOL$	0.448	0.116	0.148	0.122	0.647	0.445
$BVOL$	0.121	0.058	0.228	0.066	0.486	0.230
$ASK02$	0.795	0.149	2.223	0.118	1.206	0.141
$BID02$	-0.595	0.231	-2.905	0.139	-1.720	0.205
$ASK05$	0.330	0.100	0.244	0.080	0.456	0.110
$BID05$	-0.782	0.177	-0.531	0.101	-1.126	0.163
$ASK10$	0.083	0.059	0.019	0.050	0.111	0.085
$BID10$	-0.285	0.122	-0.240	0.066	-0.676	0.117
$ASK50$	7.823	1.398	-0.977	1.031	-1.840	3.267
$BID50$	0.904	2.151	-9.608	1.981	0.126	4.438
$ASK90$	3.692	1.022	-0.561	0.986	2.637	5.610
$BID90$	1.123	1.181	-0.511	2.331	2.389	2.453
$SPRD$	-0.003	0.009	0.093	0.029	-0.217	0.211
DMQ	-0.489	0.009	-1.193	0.022	-1.152	0.117
$QASK$	-0.027	0.028	-0.057	0.026	-0.170	0.076

Table VIII
Estimates of the Buy-Sell Pressure based on ACI specification (3)

This table gives the estimates of the difference $\gamma^B - \gamma^S$. The estimates and corresponding standard errors are computed based on the estimates of ACI specification (3) reported in the Tables IV through VI.

	NAB		BHP		MIM	
	est.	S.E.	est.	S.E.	est.	S.E.
$CLOPVOL$	0.023	0.017	0.200	0.054	-0.139	0.056
$CLOPPR$	-11.626	2.419	-3.890	1.805	-17.168	6.122
$CLBAL$	0.020	0.061	-0.189	0.064	-0.463	0.194
$TRVB$	-0.017	0.008	-0.012	0.007	0.023	0.020
$TRVS$	-0.027	0.008	-0.031	0.007	-0.028	0.020
$AVOL$	0.541	0.139	0.400	0.142	-0.291	0.490
$BVOL$	0.079	0.069	0.215	0.079	0.033	0.269
$ASK02$	0.898	0.162	3.184	0.126	1.427	0.149
$BID02$	-0.435	0.249	-3.921	0.133	-2.401	0.237
$ASK05$	0.354	0.106	0.305	0.088	0.523	0.110
$BID05$	-1.031	0.196	-0.623	0.113	-1.504	0.165
$ASK10$	0.108	0.063	0.002	0.055	0.127	0.088
$BID10$	-0.217	0.130	-0.177	0.074	-0.959	0.119
$ASK50$	7.715	1.655	-1.040	1.281	-0.570	3.470
$BID50$	0.964	2.422	-9.607	2.369	-5.181	4.969
$ASK90$	3.848	1.121	-0.613	1.192	6.150	5.942
$BID90$	1.134	1.260	-0.532	2.833	2.865	2.712
$SPRD$	-0.037	0.012	0.033	0.043	0.127	0.291
DMQ	-0.628	0.014	-1.351	0.032	-1.410	0.201
$QASK$	0.085	0.027	0.104	0.026	0.039	0.069

Table IX
Estimates of ARMA-GARCH models for trade-to-trade returns of the NAB stock

This table gives the estimates of ARMA(1,1)-GARCH(1,1) specifications of the process $\tilde{r}_i := r_i/s_i$, $i = 1, \ldots, n$, where $r_i = (\ln(mq_i) - \ln(mq_{i-1}))/\sqrt{dt_i}$ denotes the log midquote trade-to-trade return standardized by the corresponding trade duration $dt_i := t_i - t_{i-1}$. s_i denotes a seasonality components which is estimated based on a cubic spline function for the $|r_i|$ series based on one hour knots. The model is specified as

$$\tilde{r}_i = c + a(\tilde{r}_{i-1} - x'_{1,i-1}\gamma_1) + bu_{i-1} + x'_{1,i}\gamma_1 + u_i, \qquad u_i \sim N(0, h_i)$$

$$h_i = \exp\left(\omega + \alpha\frac{|u_{i-1}|}{\sqrt{h_{i-1}}} + \beta(\ln h_{i-1} - x'_{2,i-1}\gamma_2) + x_{2,i}\gamma_2\right),$$

where $x_{1,i}$ and $x_{2,i}$ denote vectors of regressors included in the conditional mean and variance function respectively, and γ_1 and γ_2 the corresponding coefficient vectors. The included regressors correspond to the covariates as defined in Table II. Moreover, $\hat{\Delta}_i := \hat{\lambda}^B(t_i; \mathcal{F}_{t_i}) - \hat{\lambda}^S(t_i; \mathcal{F}_{t_i})$ denotes the estimated excess intensity based on estimates of $\lambda^B(t_i; \mathcal{F}_{t_i})$ and $\lambda^S(t_i; \mathcal{F}_{t_i})$ using ACI specification (3).
The model is estimated by quasi maximum likelihood (QML) where the standard errors are computed based on robust estimates of the covariance matrix. The sample includes all transactions of the NAB stock during July 2002. The time series are re-initialized at each trading day. Moreover, all overnight returns are excluded.

	(1)		(2)		(3)		(4)		(5)	
	est.	S.E.	est.	S.E.	est.	S.E.	est.	S.E.	est.	S.E.
					Conditional mean function					
c	0.019	0.012	0.067	0.013	0.031	0.021	0.021	0.022	0.109	0.022
a	0.080	0.054	0.314	0.075	0.273	0.081	0.233	0.079	0.261	0.084
b	-0.147	0.054	-0.353	0.074	-0.312	0.080	-0.274	0.078	-0.294	0.084
$\ln(dt_i)$	-0.003	0.004	-0.035	0.004	-0.026	0.004	-0.020	0.004	-0.032	0.003
$\ln(dt_{i-1})$	-0.004	0.002	0.008	0.003	0.007	0.003	0.003	0.003	0.004	0.003
$\hat{\Delta}_{i-1}$			0.363	0.023	0.349	0.027	0.290	0.029	0.332	0.023
$\|\hat{\Delta}_{i-1}\|$			-0.053	0.026	-0.032	0.029	-0.066	0.033	-0.065	0.025
$SPRD_{i-1}$					-0.022	0.003	-0.025	0.003	-0.015	0.003
TRV_{i-1}					0.011	0.002	0.011	0.002	0.010	0.002
BUY_{i-1}					-0.005	0.010	-0.013	0.010	-0.031	0.009
$AVOL_{i-1}$							-0.074	0.028	-0.043	0.020
$BVOL_{i-1}$							0.024	0.015	0.046	0.012
$ASK02_{i-1}$							1.403	0.073	1.399	0.060
$BID02_{i-1}$							-1.458	0.089	-2.466	0.067
$CLOPPR$									-0.000	0.000
$CLOPVOL$									-0.001	0.003
					Conditional variance function					
ω	0.604	0.010	0.246	0.006	0.155	0.007	0.172	0.008	-0.086	0.001
α	0.298	0.003	0.245	0.002	0.209	0.003	0.220	0.003	0.142	0.002
β	0.689	0.004	0.831	0.002	0.848	0.002	0.807	0.005	0.974	0.000
$\ln(dt_i)$	-0.843	0.002	-0.865	0.003	-0.869	0.003	-0.879	0.003	-0.902	0.004
$\ln(dt_{i-1})$	-0.022	0.002	-0.012	0.002	-0.007	0.002	0.008	0.003	0.014	0.003
$\hat{\Delta}_{i-1}$			-0.977	0.013	-0.856	0.018	-1.028	0.019	-0.810	0.019
$\|\hat{\Delta}_{i-1}\|$			0.765	0.017	0.686	0.022	0.819	0.020	0.611	0.021
$SPRD_{i-1}$					0.053	0.002	0.006	0.004	0.038	0.004
TRV_{i-1}					0.091	0.002	0.084	0.002	0.073	0.003
BUY_{i-1}					-0.184	0.006	-0.186	0.007	0.024	0.009
$AVOL_{i-1}$							-0.138	0.032	-0.307	0.075
$BVOL_{i-1}$							-0.475	0.018	-1.228	0.041
$ASK02_{i-1}$							2.430	0.047	2.686	0.073
$BID02_{i-1}$							0.784	0.077	1.868	0.097
$\|CLOPPR\|$									0.037	0.000
$CLOPVOL$									-0.025	0.003
OBS	24715		24715		24715		24715		24715	
LLH	-43075		-42402		-42161		-41483		-40462	
BIC	-43126		-42473		-42263		-41625		-40624	

Table X
Estimates of ARMA-GARCH models for trade-to-trade returns of the BHP stock

This table gives the estimates of ARMA(1,1)-GARCH(1,1) specifications of the process $\tilde{r}_i := r_i/s_i$, $i = 1,\ldots,n$, where $r_i = (\ln(mq_i) - \ln(mq_{i-1}))/\sqrt{dt_i}$ denotes the log midquote trade-to-trade return standardized by the corresponding trade duration $dt_i := t_i - t_{i-1}$. s_i denotes a seasonality components which is estimated based on a cubic spline function for the $|r_i|$ series based on one hour knots. The model is specified as

$$\tilde{r}_i = c + a(\tilde{r}_{i-1} - x'_{1,i-1}\gamma_1) + bu_{i-1} + x'_{1,i}\gamma_1 + u_i, \qquad u_i \sim N(0,h_i)$$

$$h_i = \exp\left(\omega + \alpha\frac{|u_{i-1}|}{\sqrt{h_{i-1}}} + \beta(\ln h_{i-1} - x'_{2,i-1}\gamma_2) + x_{2,i}\gamma_2\right),$$

where $x_{1,i}$ and $x_{2,i}$ denote vectors of regressors included in the conditional mean and variance function respectively, and γ_1 and γ_2 the corresponding coefficient vectors. The included regressors correspond to the covariates as defined in Table II. Moreover, $\hat{\Delta}_i := \hat{\lambda}^B(t_i;\mathcal{F}_{t_i}) - \hat{\lambda}^S(t_i;\mathcal{F}_{t_i})$ denotes the estimated excess intensity based on estimates of $\lambda^B(t_i;\mathcal{F}_{t_i})$ and $\lambda^S(t_i;\mathcal{F}_{t_i})$ using ACI specification (3).
The model is estimated by quasi maximum likelihood (QML) where the standard errors are computed based on robust estimates of the covariance matrix. The sample includes all transactions of the BHP stock during July 2002. The time series are re-initialized at each trading day. Moreover, all overnight returns are excluded.

	(1)		**(2)**		**(3)**		**(4)**		**(5)**	
	est.	S.E.	est.	S.E.	est.	S.E.	est.	S.E.	est.	S.E.
Conditional mean function										
c	-0.082	0.008	-0.047	0.003	-0.139	0.016	-0.114	0.024	-0.066	0.023
a	0.260	0.021	0.810	0.008	0.510	0.027	0.095	0.052	0.123	0.057
b	-0.365	0.019	-0.846	0.007	-0.565	0.024	-0.140	0.051	-0.162	0.057
$\ln(dt_i)$	0.018	0.004	0.032	0.003	0.025	0.003	0.006	0.003	0.005	0.003
$\ln(dt_{i-1})$	0.019	0.004	0.028	0.003	0.021	0.003	0.014	0.003	0.014	0.003
$\hat{\Delta}_{i-1}$			0.439	0.007	0.412	0.010	0.102	0.005	0.134	0.006
$\vert\hat{\Delta}_{i-1}\vert$			-0.111	0.009	-0.101	0.012	0.061	0.004	0.021	0.005
$SPRD_{i-1}$					0.020	0.015	0.053	0.013	0.034	0.015
TRV_{i-1}					0.013	0.002	0.011	0.002	0.009	0.002
BUY_{i-1}					-0.035	0.009	-0.056	0.008	-0.066	0.007
$AVOL_{i-1}$							-0.175	0.011	-0.200	0.011
$BVOL_{i-1}$							0.166	0.009	0.166	0.009
$ASK02_{i-1}$							1.667	0.046	1.737	0.042
$BID02_{i-1}$							-2.420	0.075	-2.415	0.064
$CLOPPR$									0.000	0.000
$CLOPVOL$									0.007	0.005
Conditional variance function										
ω	0.340	0.005	0.363	0.005	0.145	0.003	0.093	0.005	-0.039	0.002
α	0.219	0.001	0.291	0.002	0.210	0.002	0.229	0.003	0.205	0.003
β	0.850	0.001	0.837	0.001	0.872	0.001	0.828	0.003	0.894	0.001
$\ln(dt_i)$	-0.859	0.002	-0.902	0.002	-0.903	0.002	-0.927	0.003	-0.950	0.003
$\ln(dt_{i-1})$	-0.187	0.001	-0.172	0.002	-0.173	0.002	-0.140	0.002	-0.104	0.002
$\hat{\Delta}_{i-1}$			-0.034	0.004	-0.015	0.005	0.073	0.006	0.038	0.006
$\vert\hat{\Delta}_{i-1}\vert$			-0.396	0.004	-0.389	0.005	-0.642	0.006	-0.539	0.006
$SPRD_{i-1}$					0.287	0.004	0.133	0.005	0.168	0.005
TRV_{i-1}					0.068	0.001	0.062	0.002	0.063	0.002
BUY_{i-1}					0.219	0.004	0.127	0.005	0.065	0.005
$AVOL_{i-1}$							-0.505	0.021	-0.360	0.021
$BVOL_{i-1}$							0.061	0.011	-0.341	0.012
$ASK02_{i-1}$							3.186	0.025	3.020	0.031
$BID02_{i-1}$							4.640	0.048	4.091	0.045
$\vert CLOPPR\vert$									0.034	0.000
$CLOPVOL$									0.282	0.005
OBS	29591		29591		29591		29591		29591	
LLH	-55612		-54727		-54441		-52435		-51952	
BIC	-55664		-54799		-54546		-52579		-52117	

Table XI
Estimates of ARMA-GARCH models for trade-to-trade returns of the MIM stock

This table gives the estimates of ARMA(1,1)-GARCH(1,1) specifications of the process $\tilde{r}_i := r_i/s_i$, $i = 1, \ldots, n$, where $r_i = (\ln(mq_i) - \ln(mq_{i-1}))/\sqrt{dt_i}$ denotes the log midquote trade-to-trade return standardized by the corresponding trade duration $dt_i := t_i - t_{i-1}$. s_i denotes a seasonality components which is estimated based on a cubic spline function for the $|r_i|$ series based on one hour knots. The model is specified as

$$\tilde{r}_i = c + a(\tilde{r}_{i-1} - x'_{1,i-1}\gamma_1) + bu_{i-1} + x'_{1,i}\gamma_1 + u_i, \qquad u_i \sim N(0, h_i)$$

$$h_i = \exp\left(\omega + \alpha\frac{|u_{i-1}|}{\sqrt{h_{i-1}}} + \beta(\ln h_{i-1} - x'_{2,i-1}\gamma_2) + x_{2,i}\gamma_2\right),$$

where $x_{1,i}$ and $x_{2,i}$ denote vectors of regressors included in the conditional mean and variance function respectively, and γ_1 and γ_2 the corresponding coefficient vectors. The included regressors correspond to the covariates as defined in Table II. Moreover, $\hat{\Delta}_i := \hat{\lambda}^B(t_i; \mathcal{F}_{t_i}) - \hat{\lambda}^S(t_i; \mathcal{F}_{t_i})$ denotes the estimated excess intensity based on estimates of $\lambda^B(t_i; \mathcal{F}_{t_i})$ and $\lambda^S(t_i; \mathcal{F}_{t_i})$ using ACI specification (3).
The model is estimated by quasi maximum likelihood (QML) where the standard errors are computed based on robust estimates of the covariance matrix. The sample includes all transactions of the MIM stock during July 2002. The time series are re-initialized at each trading day. Moreover, all overnight returns are excluded.

	(1)		**(2)**		**(3)**		**(4)**		**(5)**	
	est.	S.E.	est.	S.E.	est.	S.E.	est.	S.E.	est.	S.E.
	Conditional mean function									
c	-0.442	0.125	-0.439	0.227	-0.012	0.009	0.179	0.170	-0.196	0.053
a	0.126	0.228	0.136	0.438	0.965	0.014	0.119	0.203	0.546	0.049
b	-0.145	0.226	-0.145	0.435	-0.967	0.013	-0.132	0.200	-0.573	0.046
$\ln(dt_i)$	0.052	0.014	0.048	0.013	-0.019	0.014	-0.001	0.012	-0.002	0.006
$\ln(dt_{i-1})$	0.074	0.010	0.088	0.010	0.059	0.012	0.005	0.010	-0.008	0.006
$\hat{\Delta}_{i-1}$			0.385	0.028	0.483	0.040	0.179	0.041	0.078	0.012
$\lvert\hat{\Delta}_{i-1}\rvert$			0.023	0.041	0.006	0.040	0.025	0.034	0.095	0.013
$SPRD_{i-1}$					-0.133	0.133	-0.635	0.180	0.355	0.109
TRV_{i-1}					0.024	0.008	0.010	0.007	-0.012	0.002
BUY_{i-1}					0.186	0.027	0.039	0.030	-0.001	0.012
$AVOL_{i-1}$							0.060	0.040	-0.851	0.017
$BVOL_{i-1}$							0.266	0.021	0.011	0.009
$ASK02_{i-1}$							0.909	0.051	1.250	0.027
$BID02_{i-1}$							-0.043	0.205	-0.916	0.072
$CLOPPR$									0.024	0.001
$CLOPVOL$									-0.068	0.001
	Conditional variance function									
ω	2.070	0.069	1.619	0.055	0.736	0.036	0.325	0.024	-0.061	0.001
α	0.420	0.016	0.424	0.015	0.337	0.012	0.205	0.009	0.150	0.002
β	0.674	0.010	0.721	0.008	0.799	0.007	0.842	0.008	0.998	0.000
$\ln(dt_i)$	-1.158	0.002	-1.134	0.004	-1.106	0.004	-1.057	0.005	-0.935	0.006
$\ln(dt_{i-1})$	-0.176	0.004	-0.149	0.005	-0.155	0.006	-0.199	0.005	-0.101	0.005
$\hat{\Delta}_{i-1}$			-0.014	0.012	-0.087	0.016	0.145	0.017	-0.023	0.019
$\lvert\hat{\Delta}_{i-1}\rvert$			0.308	0.018	0.233	0.023	-0.129	0.019	0.199	0.025
$SPRD_{i-1}$					0.598	0.080	-0.322	0.079	-0.577	0.068
TRV_{i-1}					0.164	0.003	0.189	0.003	0.155	0.004
BUY_{i-1}					-0.107	0.016	-0.152	0.015	-0.055	0.020
$AVOL_{i-1}$							-0.401	0.057	-13.466	0.140
$BVOL_{i-1}$							-1.353	0.057	-2.611	0.114
$ASK02_{i-1}$							1.904	0.041	2.564	0.036
$BID02_{i-1}$							2.711	0.049	2.846	0.045
$\lvert CLOPPR\rvert$									0.427	0.025
$CLOPVOL$									-0.136	0.018
OBS	3839		3839		3839		3839		3839	
LLH	-8579		-8616		-8472		-7692		-7475	
BIC	-8620		-8554		-8437		-7701		-7503	

B Figures

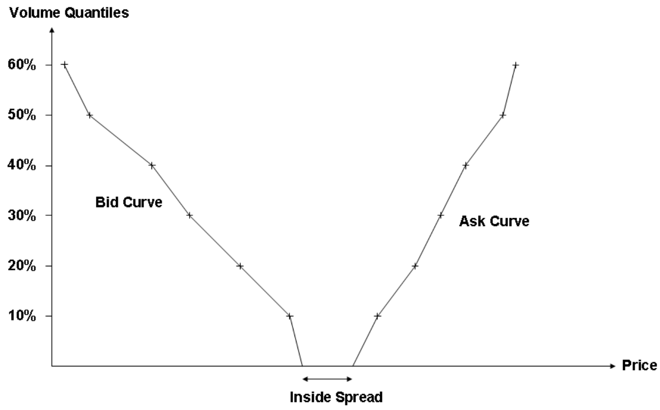

Figure 1. Hypothetical market reaction curves. A graphical illustration of the price-volume relationship on the bid and ask side of the market.

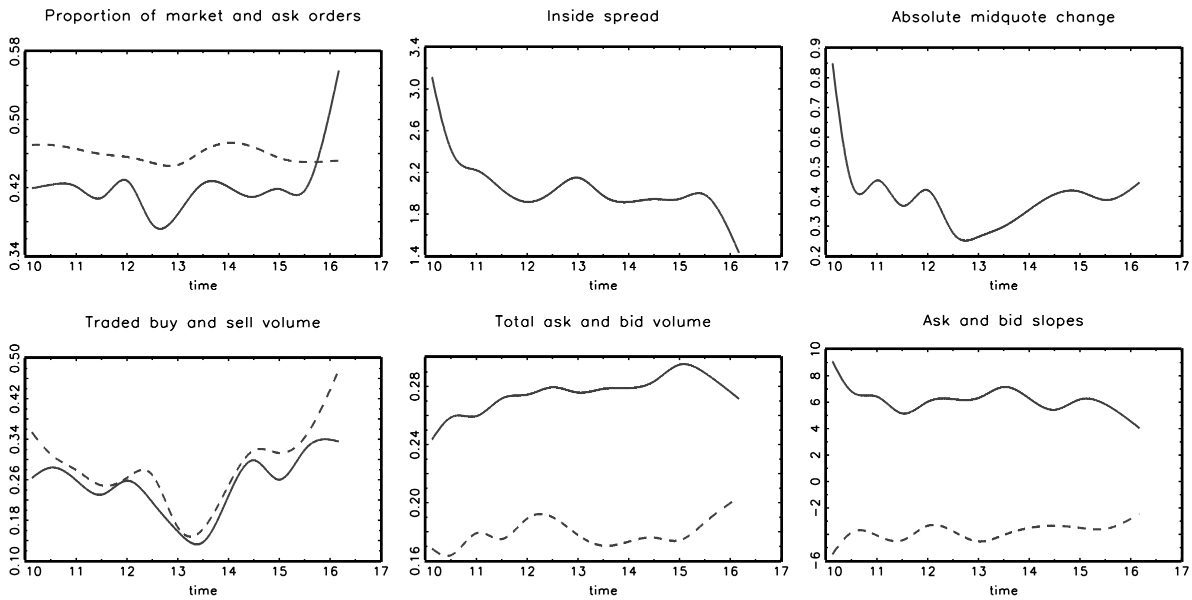

Figure 2. Intraday seasonality functions of different order book variables for the NAB stock. Upper left: Proportion of market vs. limit orders (solid line) and of ask vs. bid orders (dotted line). Upper middle: Difference between the best ask and bid price. Upper right: Absolute mid-quote change between consecutive order arrivals. Lower left: Traded volume (divided by 10^4) on the buy side (solid line) and the sell side (dotted line). Lower middle: Total volume (divided by 10^6) on the ask queue (solid line) and on the bid queue (dotted line). Lower right: Ask and bid slopes, ASK05 (solid line) and BID05 (dotted line). Seasonality functions estimated based on cubic spline regressions using one hour knots.

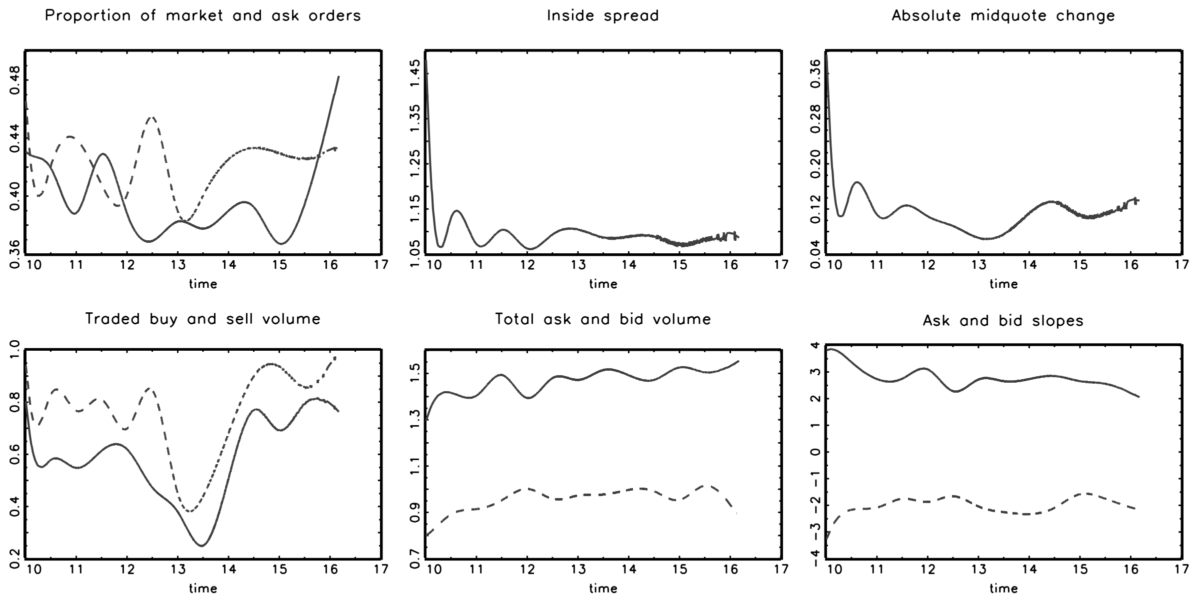

Figure 3. Intraday seasonality functions of different order book variables for the BHP stock. Upper left: Proportion of market vs. limit orders (solid line) and of ask vs. bid orders (dotted line). Upper middle: Difference between the best ask and bid price. Upper right: Absolute mid-quote change between consecutive order arrivals. Lower left: Traded volume (divided by 10^4) on the buy side (solid line) and the sell side (dotted line). Lower middle: Total volume (divided by 10^6) on the ask queue (solid line) and on the bid queue (dotted line). Lower right: Ask and bid slopes, ASK05 (solid line) and BID05 (dotted line). Seasonality functions estimated based on cubic spline regressions using one hour knots.

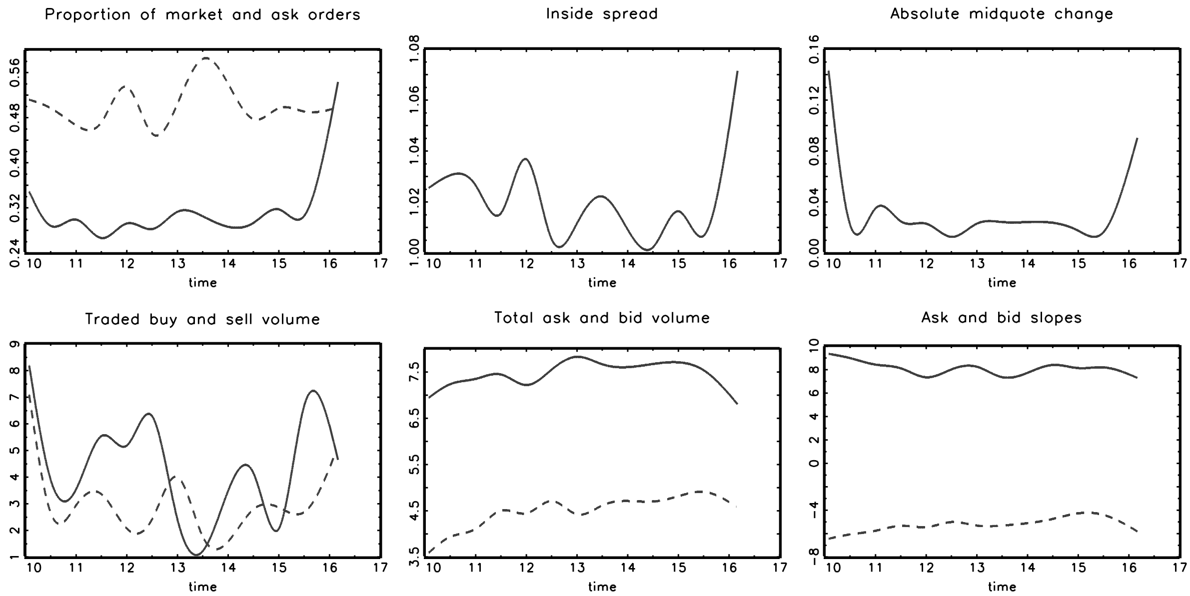

Figure 4. Intraday seasonality functions of different order book variables for the MIM stock. Upper left: Proportion of market vs. limit orders (solid line) and of ask vs. bid orders (dotted line). Upper middle: Difference between the best ask and bid price. Upper right: Absolute mid-quote change between consecutive order arrivals. Lower left: Traded volume (divided by 10^4) on the buy side (solid line) and the sell side (dotted line). Lower middle: Total volume (divided by 10^6) on the ask queue (solid line) and on the bid queue (dotted line). Lower right: Ask and bid slopes, ASK05 (solid line) and BID05 (dotted line). Seasonality functions estimated based on cubic spline regressions using one hour knots.

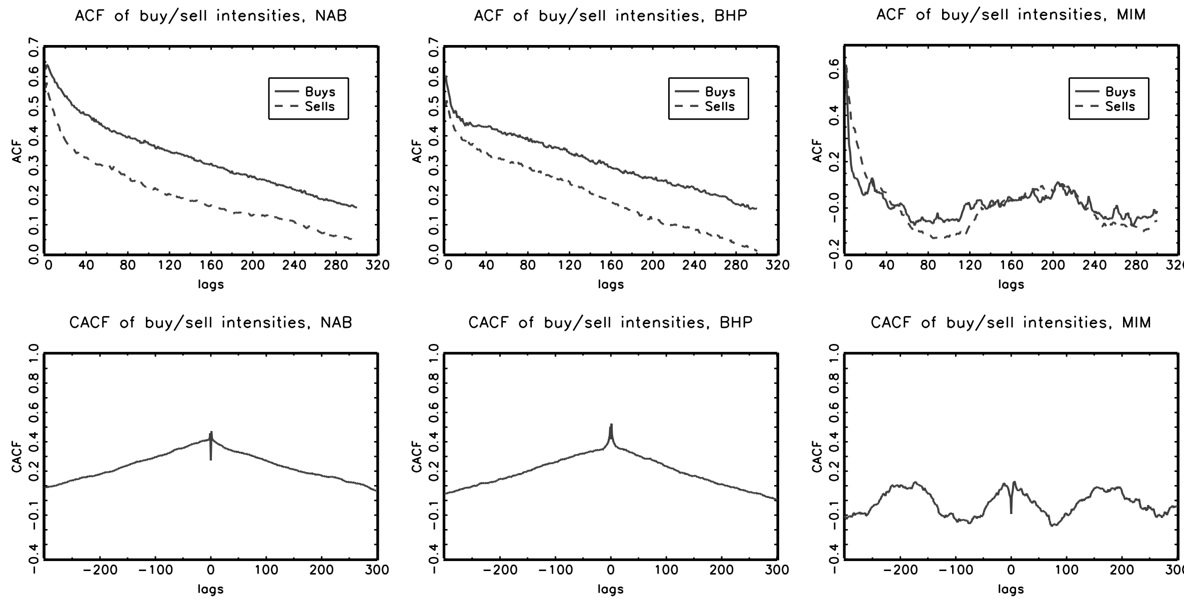

Figure 5. Empirical autocorrelation and cross-autocorrelation functions of the estimated buy and sell intensities. The estimates of the intensity functions are based on the estimates of the ACI specification (3) in Tables IV through VI. The autocorrelation functions (ACF) and cross-autocorrelation functions (CACF) of the estimated buy and sell intensities are evaluated at each trade arrival t_i. Left panel: NAB, middle panel: BHP, right panel: MIM.

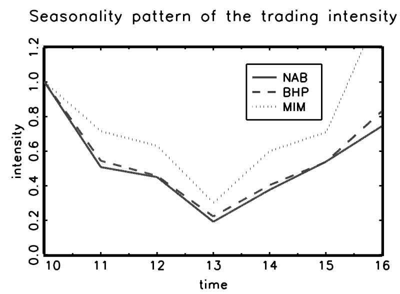

Figure 6. Estimated intraday seasonality function of the estimated buy and sell intensity. The estimates are based on ACI specification (3) in Tables IV through VI. Solid line: NAB, broken line: BHP, dotted line: MIM.

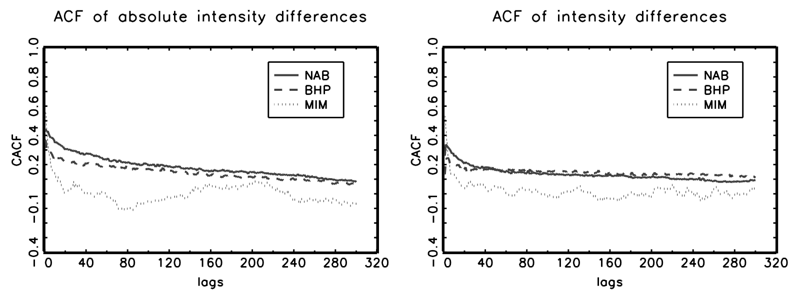

Figure 7. Empirical autocorrelation functions of the estimated absolute and plain buy-sell excess intensity ($|\Delta_i|$ and Δ_i). The estimates of $|\Delta_i|$ and Δ_i are based on ACI specification (3). The empirical autocorrelation functions of $|\Delta_i|$ and Δ_i are evaluated at each trade arrival t_i. Solid line: NAB, broken line: BHP, dotted line: MIM.