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Modelling the buy and sell intensity in a limit order book market ☆

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Abstract

In this paper, we model the buy and sell arrival process in the limit order book market at the Australian Stock Exchange. Using a bivariate autoregressive intensity model we analyze the contemporaneous buy and sell intensity as a function of the state of the market. We find evidence that trading decisions are both information as well as liquidity driven. Confirming predictions from market microstructure theory traders submit market orders by inferring from the recent order flow and the book with respect to upper and lower tail expectations as well as trading directions. However, traders also tend to take liquidity when the liquidity supply is high. Moreover, we find

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evidence that traders pay more attention to recent order arrivals and the current state of the order book than to the past order flow.

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1. Introduction

Limit order book data can be regarded as the informational limit case of financial data. They provide detailed characteristics about the complete order process allowing the study of trading activity on the lowest possible level of disaggregation. An important objective of research into trading systems is to obtain a deep understanding of how much information is provided by an open limit order book market as compared to systems where only the best quotes are observable. A fundamental question is whether (or not) traders use the information provided by the book and thus whether their trading strategies are influenced by the state of the market. The aim of this paper is to analyze whether the state of the order book and recent order arrivals influence traders' decisions on when to trade and the side of the market on which to trade. The recent literature typically addresses these questions by using either univariate duration models or competing risks models.[1] Using different data and different explanatory variables to capture the state of the market these studies reach conflicting conclusions on whether the state of the book determines the choice of the market side on which to trade and whether or not it impacts the timing of an order submission.

The main contributions of this paper are twofold. Firstly, the use of a multivariate dynamic continuous time setting allows us to investigate these research questions in a framework that extends previous approaches. The key innovation in this paper is to model the buy and sell arrival processes in terms of their intensities corresponding to the instantaneous arrival rates of buy or sell transactions per unit of time. By using a bivariate dynamic intensity model we estimate the contemporaneous buy and sell intensities at each instant of time. This approach requires no aggregation over time and overcomes the problem that buy and sell transactions are not equally spaced in time and may occur asynchronously. Moreover, in this model it is straightforward to allow for time-varying covariates to capture limit order arrivals between consecutive transactions and thus *any* changes in the limit order book. The (log) ratio between the estimated contemporaneous buy and sell intensities yields a readily interpretable measure of the continuous net buy pressure in the market. Such a measure allows the characterization of market periods in which traders have a strong preference for one-sided trading.

Secondly, we use a unique data set extracted by replicating the fully automatic execution engine of the Australian Stock Exchange (ASX). We are able to identify exactly buyer or

[1]See, for example, Bisière and Kamionka (2000), Coppejans and Domowitz (2002), Lo and Sapp (2003) or Pascual and Veredas (2004).

seller initiated trades, and to reconstruct the order book completely and distinctly at each instant of time. Based on this data, it is possible to quantify the buy and sell intensities and their dependence on the state of the market, as characterized by the standing buy and sell volume, the ask and bid depth, and the characteristics of incoming market and limit orders.

The buy and sell intensities are modelled using a bivariate version of the autoregressive conditional intensity (ACI) model proposed by Russell (1999). We extend the ACI model to account for the changes in the limit order book caused by a new limit order, a change in an existing limit order or a cancellation of a limit order. As limit orders naturally arrive during the interval between two consecutive trades, these order book and limit order characteristics are modelled as time-varying covariates.

Our empirical analysis is based on order data over nearly two months for five stocks traded at the ASX. Over all stocks, we utilize detail information based on more than 330,000 individual observations. Our results show that trading decisions are both information as well as liquidity driven. On one hand, traders submit market orders after making inferences from the recent order flow and the state of the book with respect to the existence of information and market participants' price expectations according to theoretical predictions like those derived by Glosten (1994). On the other hand, traders also tend to refrain from trading when the liquidity supply is low and to take liquidity when the supply is high. In particular, we find that the net buy pressure increases after the arrival of large buy market orders and that it decreases after large sell market orders. We even observe that the magnitude of the marginal effects of order volumes increases with the traded quantity. On the other hand, slight evidence for a weakening of these effects is observed if incoming market orders completely clear one or several levels of the opposite queue implying upward (downward) shifts of the best ask (bid) quotes. Hence, traders refrain from trading when they face higher transactions costs due to worse terms of trade.

Furthermore, we find a significant rise in the net buy pressure when the ask side reflects a lower depth as characterized by a greater dispersion in posted limit orders. This effect confirms Glosten's (1994) notion that pending limit prices reflect investor's upper or lower tail expectations. However, it turns out that only the price-volume relation close to the best bid and ask quotes has a significant influence on traders' buy-sell decisions. Moreover, in contrast to theoretical predictions, we observe an increase of the net buy pressure when an entering limit order is placed below (above) the best ask (bid) quote. This indicates that traders tend to take liquidity when liquidity supply is high. Furthermore, our results reveal only limited evidence for a significant influence of market activities during the last 30 min on the buy and sell intensity. This finding indicates that the state of the market seems to be sufficiently conveyed by the current state of the limit order book. Finally, we find clear evidence for interdependences between the buy and sell side. Thus, traders' preference for immediacy on one particular market side is not only influenced by the state of the book on the same side, but also by that on the opposite side.

The recent literature on limit order book trading is characterized by a growing body of empirical studies. One main strand of this literature focusses on the information content of the limit order book,[2] whereas another branch of the literature is concerned with traders'

[2] See, for example, Biais et al. (1995), Corwin and Lipson (2000), Cao et al. (2003), Pascual and Veredas (2004) or recently Harris and Panchapagesan (2005).

submission strategies[3] and order aggressiveness.[4] The papers closest to our study are Hedvall et al. (1997) who focus on buy and sell market orders as well and, from a methodological viewpoint, the papers by Coppejans and Domowitz (2002) and Pascual and Veredas (2004) who both utilize a duration framework but provide conflicting empirical evidence as to whether the order book beyond the inside spread is informative for the timing of quotes. Hall and Hautsch (2006) use a six-dimensional ACI specification to model the processes of market orders, limit orders and cancellations at the ASX. However, in order to keep their model computationally tractable they focus exclusively on large-size, aggressive market orders, limit orders and cancellations. A further paper which is relatively close to our approach is the study by Large (2006) who applies a high-dimensional Hawkes process to model the order book process of one stock at the London Stock Exchange. While he is also emphasizing the advantages of a continuous-time setting, his focus is rather on the analysis of the resiliency of the book than on the net buy pressure. However, none of the aforementioned approaches models the continuous trading intensity as a function of a completely reconstructed limit order book. By utilizing a huge amount of detail information regarding the state of the market and by accounting for any changes of the book, this paper fills this gap in the literature and allows deeper insights into the question of which pieces of the order book are informative for the decision of when and where to submit market orders.

The remainder of the paper is organized in the following way: in Section 2 we give an overview of the electronic trading system at the ASX, and in Section 3 testable economic hypotheses are formulated. Section 4 presents the methodological framework, and in Section 5 we describe the data base as well as the explanatory variables employed in the analysis. Section 6 presents the empirical results, and Section 7 concludes.

2. Limit order book trading at the Australian Stock Exchange

The Australian Stock Exchange (ASX) is a continuous double auction electronic market with trading rules that are similar to other electronic limit order markets operating in Paris, Hong Kong and Sao Paulo.[5] The continuous auction trading period is preceded and followed by a call auction. The exact opening times are randomized from 10:00 a.m., but normal trading takes place continuously on all stocks between 10:09 a.m. and 4:00 p.m. from Monday to Friday. The market opens with a call auction market in all stocks. From 7:00 a.m. each trading day traders are permitted to enter public quotes until the call auction after which the market is open for continuous trading. An overview of the trading rules is given in Table 1.

When the ASX is in normal trading mode, any buy (sell) order entered that has a price that is greater than (less than) or equal to existing queued buy (sell) orders will execute immediately. Trades will be generated and traded orders deleted until there is no more buy (sell) order volume that has a price that is equal to or greater (less) than the entered buy (sell) order. If the order volume cannot be executed completely, the remaining volume

[3]See, for example, Hollifield et al. (2004), Hollifield et al. (2003), Ahn et al. (2001) or Bloomfield et al. (2005).

[4]See, for example, Griffiths et al. (2000), Al-Suhaibani and Kryzanowski (2000), Ranaldo (2004), Pascual and Veredas (2004) or Hall and Hautsch (2006).

[5]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.

Table 1
Daily 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 a.m.–7:00 a.m.	Enquiry on current orders only.
Market pre-open	7:00 a.m.–10:00 a.m.	Can enter, delete and amend orders and enter off-market trades.
Market opening	10:00 a.m.–10:09 a.m.	Staggered call auctions open continuous trading.
Normal market	10:09 a.m.–4:00 p.m.	Can enter, amend and delete orders. Overlapping buy and sell orders execute immediately.
Closing call auction	4:05 p.m. (±15 s random)	Can enter, delete and amend orders prior to the closing call auction.
Late trading	4:05 p.m.–5:00 p.m.	Can enter, delete and amend orders. Late trades permitted with restrictions.
Market closed	5:00 p.m.–7:00 p.m.	Can only delete orders.

enters the queues as a limit order. When a market order executes against several standing limit orders, the ASX generates a trade record for each market order—limit order pair of executing orders. In this case we aggregate all multiple trade records generated by a single market order into a single trade record.

Limit orders are queued in the buy and sell queues according to a strict price-time priority order. Between 7:00 a.m. and 5:00 p.m., 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 an order price so that it overlaps the opposite order queue will cause an immediate full 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). Other price modifications result in the order moving to the lowest time priority within the new price level.

The minimum tick size varies with the stock price. The schedule is that for order prices below 10 cents, the tick size is 0.1 cents, for order prices above 10 cents and below 50 cents it is 0.5 cents, and for orders priced 50 cents and above it is 1 cent. 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 $AUD200,000. This is a typical feature of many exchanges, such as the Paris Bourse.[6] Nevertheless, although undisclosed volume orders are permitted, sufficient information is available to unambiguously reconstruct all transactions.

Trades reported to the market that are not executed through the SEATS system are designated as "Off-Market Trades." There are three main generators of these 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.

[6]See Biais et al. (1995), and Pardo and Pascual (2004) for an analysis of the impact of hidden orders on liquidity.

3. Economic framework and testable hypotheses

A seminal contribution to the theoretical literature on limit order book markets is the paper by Glosten (1994) which is extended in several directions by Chakravarty and Holden (1995), Handa and Schwartz (1996), Seppi (1997), Kavajecz (1999), Viswanathan and Wang (2002) and Parlour and Seppi (2003). In this section, we briefly review Glosten's model which we use as an underlying general framework to derive testable economic hypotheses regarding the impact of the state of the market on the buy and sell intensity.

Glosten models a market environment in which all market participants have access to an electronic screen. Posting limit orders is done costlessly and the execution of a trade against the book occurs in a "discriminatory" fashion, i.e., each limit order transacts at its limit price. Investors who trade against the book are rational and risk averse and maximize a quasi-concave utility function of their cash and share position as well as (unknown) personal preferences. The trading behavior of market order traders depends on their marginal valuation functions and the prevailing terms of trade, i.e., the list of bid and ask quotes available, which influence the changes in investors' cash and share positions. It is assumed that an investor chooses the trade quantity such that his marginal valuation equals the marginal price corresponding to the price paid for the last share in a transaction. There is informed trading if an investor's marginal valuation is affiliated with the future payoff. Then, incoming market orders reveal information about the unknown "full information value" of the traded security. Due to the anonymity of the electronic market, the underlying marginal valuation implied by an arriving market order can be assessed by the liquidity suppliers only through the observed limit price and the traded quantity given the terms of trades offered by the book. Glosten assumes that there is a large number of uninformed, risk-neutral and profit-maximizing limit order submitters who set limit prices and quantities on the basis of their "upper tail expectation." The latter corresponds to the conditional expectation of the asset's full information liquidation value given that the next arrival's marginal valuation is greater than or equal to the traded quantity. In the presence of private information, liquidity suppliers protect themselves against adverse selection by setting the limit price at least equal to the upper tail expectation given a market order trading at the corresponding price. It is shown that such a strategy leads to a Nash equilibrium which is characterized by a zero-profit condition for prices at which positive quantities are offered. As a consequence of the behavior of liquidity suppliers, the limit order book itself has information content.

In order to derive testable hypotheses regarding the impact of the state of the market on the resulting (instantaneous) net buy pressure, we have to make the assumption that trading decisions themselves are not only driven by private information and/or personal characteristics but are also influenced by the trading process and the state of the book. In Glosten's framework this implies that investors infer from the book and the observed trading history in order to update their underlying expectations with respect to the full information liquidation value of the asset. Then, investors choose their trade quantities by maximizing expected utility given public information as well as the state of the market.

Below we use Glosten's framework to derive specific hypotheses which are empirically tested in Section 6. For the sake of brevity, we formulate our economic arguments mainly for the buy side of the market. The corresponding statements for the sell side are derived similarly following the same economic logic.

3.1. The impact of market order arrivals

As described in Section 2, at the ASX, market order traders have to specify the limit price and the order volume. Then, a (buy) order will be traded at successive prices only to the extent that stock is available at the specified limit price. The higher the limit price, the more likely it is that the posted volume can be fully matched. Correspondingly, the higher the posted volume given the limit price, the higher the probability that the order cannot be executed completely. Therefore, the limit price set by a trader reveals his order aggressiveness and indicates his willingness to fully execute his order by "walking up" the book. The greater the distance between the limit price set by the investor and the prevailing best ask price, the higher the trader's marginal valuation and thus his expectation of the full information liquidation value of the asset. Consequently, a high distance between the posted limit price and the current best ask quote bears "positive" information in the sense of a higher expected liquidation value and should increase the net buy pressure.

Nevertheless, if the posted volume is only small and/or the depth of the market is very high, the posted limit price as a proxy for an investor's marginal valuation can be misleading as long as the investor infers from the book that with high certainty the posted (buy) order will trade at a lower price. In such a case, the *realized* marginal price is a more reliable indicator for his marginal valuation. Therefore, the *realized* change of the best ask trade as a result of a buy should be even more informative for the net buy pressure. Nevertheless, conflicting effects might arise since a strong upward movement of the best ask price confronts subsequent investors with a reduced ask depth and worse terms of trade. Ceteris paribus, such liquidity driven effects reduce traders' incentive to post a further buy order. These opposed effects might cause non-monotonic relations between the change of the best ask/bid quote and the resulting net buy pressure. Nonetheless, we formulate the first testable hypothesis in line with the former argument:

H1: *Posted limit prices and ask/bid quote changes*

(a) *The net buy pressure increases (decreases) with the difference between the limit price set by a buyer (seller) and the prevailing best ask (bid) price.*

(b) *The net buy pressure increases (decreases) with the magnitude of the ask (bid) quote change caused by a buy (sell) transaction.*

Moreover, investors' marginal valuation is revealed not only by their posted limit price but also by the actually traded volume. According to Glosten's model traders choose the traded quantity such that the marginal valuation equals the marginal price. Therefore, a high volume reveals a high marginal valuation and should have a positive effect on the net buy pressure. This prediction is supported by Parlour (1998) who shows that in a dynamic equilibrium model changes in the execution probabilities affect traders' choices as to whether to post a market order or a limit order. This leads to systematic patterns in their order submission strategies even when there is no asymmetric information in the market.[7] The basic underlying mechanism is a "crowding out" effect whereby market orders and limit orders on the individual market sides crowd out one another when the ask or bid

[7] Handa et al. (2003) extended this approach by introducing an adverse selection component due to the presence of privately informed traders.

queue is changed. In particular, the probability of the arrival of a buy (sell) trade after observing a buy (sell) trade is higher than after observing a sell (buy) trade. This results from a buy transaction reducing the depth on the ask side which in turn increases the execution probability for limit sell orders. Hence, for a potential seller, the attractiveness of limit orders relative to market orders rises inducing a crowding out of market sell orders in favor of limit sell orders. Accordingly, we would expect a positive impact of large buy volumes on the subsequent net buy pressure. This hypothesis is also consistent with predictions from asymmetric information based market microstructure theory (see, e.g., Easley and O'Hara, 1987 or Blume et al., 1994) where the transaction volume is a proxy for the existence of information on the market.

Nevertheless, a branch of the literature stresses that informed traders tend to use a medium volume size rather than large volumes in order to hide their informational advantage.[8] Consequently, medium size volumes reveal the highest information content. In a limit order book market such a non-monotonic relationship might be amplified by the fact that high volumes reduce the depth and increase the implied transactions costs of subsequent traders. Therefore, overall we expect to observe a non-monotonic relation between the trading volume and the subsequent net buy pressure.

*H*2: *Trading volume*
The marginal impact of the buy (*sell*) *trading volume on the net buy pressure is increasing* (*decreasing*) *for small volumes and decreasing* (*increasing*) *for large volumes.*

3.2. The impact of limit order arrivals

In Glosten's framework, liquidity suppliers protect themselves against the risk of "being picked off" by setting the limit price at least equal to the upper tail expectation given a market order trading at the corresponding price. Hence, a liquidity supplier who sets the ask limit price *below* the prevailing best ask price indicates that he faces only a low adverse selection risk and that his upper tail expectation can be even lower than the most current best ask price. Consequently, this should imply a negative signaling effect and the net buy pressure is expected to decline. This prediction is in line with the implications of the model by Parlour (1998), where the thickness of the book on a particular side decreases a trader's incentive to post further limit orders on that side and leads to a higher probability of market orders on the opposite side. In contrast, a limit price which is above the current best ask quote indicates a higher upper tail expectation and thus should imply a positive signaling effect. Therefore, we expect an increasing (decreasing) net buy pressure after an arriving limit order above (below) the prevailing best ask quote. Corresponding effects are expected on the bid side of the market. Moreover, these impacts should rise with the size of the posted volume.

Furthermore, as shown by the descriptive statistics in Table 2, a considerable proportion of the incoming orders are cancellations. However, the economic implications of cancellations are less clear as long as we cannot identify the reasons that a limit order was cancelled. This is particularly true for cancelled orders with limit prices far away from the current best ask quote. Nevertheless, it is reasonable to assume that investors cancel orders close to the current best quote when they face a high adverse selection risk.

[8] See, e.g., Barclay and Warner (1993) or Kempf and Korn (1999) among others.

Table 2
Descriptive statistics of trade and limit order arrival processes at the ASX

This table gives descriptive statistics associated with the trade and limit order arrival process of the NAB, BHP, MIM, TLS and WOW stocks. The data are extracted from ASX trading. Sample period: July 8th to August 30th, 2002. Duration statistics measured in seconds. Overnight spells are ignored

	NAB	BHP	MIM	TLS	WOW
	Number of events				
Total number of events	95,523	130,397	28,285	84,594	54,304
Number of trades	38,927	54,499	8,617	35,155	22,355
Number of buys	19,878	33,414	5,148	18,276	12,417
Number of sells	19,049	21,085	3,469	16,879	9,938
Number of limit order arrivals	68,668	93,053	22,282	62,647	37,164
Number of ask orders	21,841	27,199	7,002	19,728	12,192
Number of bid orders	23,712	35,782	8,593	20,864	14,279
Number of ask cancellations	5,263	6,105	1,537	3,987	2,444
Number of bid cancellations	5,780	6,812	2,536	4,860	3,034
	Time between transactions				
Mean	21.74	15.85	98.99	23.96	37.62
Standard deviation	37.36	26.53	157.43	33.32	66.28
LB(20) statistic	23,639.17	33,285.01	4,754.90	12,287.93	23,083.82
	Time between buys				
Mean	42.58	25.85	165.32	46.10	67.75
Standard deviation	76.58	42.55	322.85	65.76	123.89
LB(20) statistic	9,697.65	23,361.04	2,107.60	6,869.28	12,176.62
	Time between sells				
Mean	44.45	40.98	245.68	49.92	84.63
Standard deviation	72.87	71.07	408.90	69.83	145.38
LB(20) statistic	10,117.39	11,599.84	679.78	6,338.48	5,928.03
	Time between limit order arrivals				
Mean	15.311	11.22	48.81	16.32	27.68
Standard deviation	154.20	128.84	279.10	160.04	212.47
LB(20) statistic	73.10	43.74	102.59	53.59	172.97
	Time between ask limit order arrivals				
Mean	38.73	31.75	121.56	42.64	68.945
Standard deviation	61.51	53.30	175.36	65.35	126.29
LB(20) statistic	12,856.82	14,685.81	4,091.07	10,272.55	9,010.26
	Time between bid limit order arrivals				
Mean	35.68	24.13	99.20	40.34	58.79
Standard deviation	60.73	38.57	157.32	58.74	113.22
LB(20) statistic	16,830.24	21,847.30	5,566.55	11,024.39	11,357.33
	Time between ask cancellations				
Mean	159.33	141.24	548.80	211.29	340.38
Standard deviation	274.18	242.77	935.47	326.59	656.53
LB(20) statistic	1,344.89	1,554.70	123.59	782.35	478.10
	Time between bid cancellations				
Mean	145.86	126.48	331.70	173.03	275.06
Standard deviation	252.12	197.66	556.54	260.67	494.70
LB(20) statistic	1,362.20	1,893.51	371.83	1,265.60	862.17

Consequently, we expect that cancellations close to the midquote reveal distinct information for the subsequent net buy pressure:

*H*3: *Limit order arrivals and cancellations*

(a) *The net buy pressure is increasing* (*decreasing*) *if an incoming ask limit order is set above* (*below*) *the most current best ask quote. Correspondingly, the net buy pressure is decreasing* (*increasing*) *if an incoming bid limit order is set below* (*above*) *the most current best bid quote. These effects are increasing with the corresponding order volume.*

(b) *The net buy pressure is increasing* (*decreasing*) *if an ask* (*bid*) *limit order close to the prevailing best ask* (*bid*) *quote is cancelled. These effects are increasing with the corresponding order volume.*

3.3. The impact of market depth and spreads

While recent market and limit order arrivals reflect the current order flow, the pending volumes and limit prices in the queues of the book characterize the current liquidity supply on each side of the market. In our empirical application we measure market depth by the steepness of the market reaction curve, which relates quantiles of the cumulated pending volume in the queue to the corresponding limit price (see Fig. 1). A central implication of Glosten's model is that the limit order book reveals information regarding liquidity suppliers' upper and lower tail expectations. In particular, a lower ask depth, as characterized by a widening of the spreads on the ask side and thus a flattening of the ask reaction curve given the pending volume, indicates that traders have higher upper tail expectations and are willing to sell their positions at comparatively higher prices. Therefore, as long as the positive signaling effect of higher upper tail expectations outweighs a deterioration of the terms of trade, we expect an increase of the net buy pressure if the price-volume ask curve given the pending ask volume is flattening out.

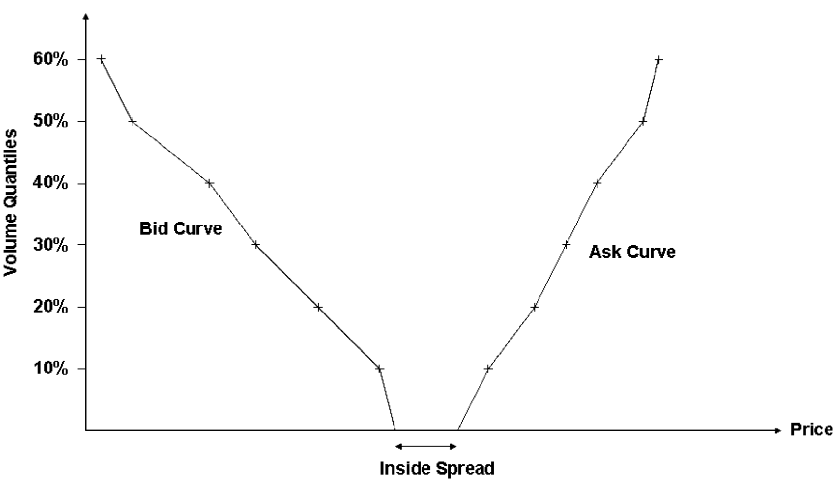

Fig. 1. Hypothetical market reaction curves. A graphical illustration of the price–volume relationship on the bid and ask side of the market.

However, the influence of the cumulated pending ask volume is less clear. As long as the relative proportions of the pending volume on the individual price levels in the queue (and therefore the steepness of the ask curve) is unchanged, the average upper tail expectations of liquidity suppliers do not change. Rather, the terms of trade improve since an investor can trade a higher quantity at the same price. Therefore, the cumulated ask volume given the ask slope should have a positive effect on the net buy pressure. Conversely, in Parlour (1998), an increase of the pending ask volume given the ask slope as well as the pending bid volume implies a crowding out effect since the execution probability of further arriving ask limit orders declines in relation to the bid side. Therefore, the incentive to post market orders on the sell side increases which implies a decline of the net buy pressure. Formulating the predictions in accordance with Parlour's model we state Hypothesis H4 as follows:

*H*4: *Ask and bid depth*

(a) *A decrease in the ask* (*bid*) *slope given the pending ask volume increases* (*decreases*) *the net buy pressure*.

(b) *An increase in the pending ask* (*bid*) *volume given the ask* (*bid*) *slope and the pending bid* (*ask*) *volume decreases* (*increases*) *the net buy pressure*.

Numerous studies focus on the inside spread as a measure for the tightness of the market.[9] The discriminatory nature of the limit order book in Glosten's model implies that limit prices are set so that on average small market orders are profitable whereas larger trades are unprofitable. In equilibrium, every offer has zero expected profit and the book expects to break even. If there is increasing adverse selection in the market, spreads increase and market order trading becomes more expensive until liquidity suppliers are on average compensated for the increased risk to be picked off. As a result, the intensity of market order trading on both sides is reduced and limit order trading becomes more profitable. The same conclusion is derived by Foucault (1999) in a dynamic game theoretical equilibrium model which allows us to derive implications for the equilibrium mix between market orders and limit orders. This leads to the following hypothesis:

*H*5: *Bid-ask spread*

A higher bid-ask spread decreases the trading intensity on both sides of the market.

3.4. The impact of the past trading activity

A reasonable assumption is that investors do not only infer from the *present* state of the book but also from recent market movements, e.g., during the last 30 min.[10] Recent market activities are best characterized by changes in the price, the (signed) order flow, and changes in the ask and bid slopes as well as variables indicating possible uncertainty in the market.

The economic implications of price changes during the last 30 minutes are unclear. On the one hand, positive price movements indicate that market order traders have high

[9]See, e.g., Cohen et al. (1981), Niemeyer and Sandås (1993), Wang (1999), Handa et al. (2003) and McCulloch (2003).

[10]This time window is used in the empirical analysis.

valuations and/or liquidity suppliers have high upper tail expectations and thus set high ask limit prices. On the other hand, a substantial price movement confronts subsequent investors with worse terms of trade which should reduce the net buy pressure. Nevertheless, overall we postulate a positive relation between the cumulative price change during the last 30 minutes and the resulting net buy pressure:

*H*6: *Past price changes*
A positive (*negative*) *price change during the last* 30 *min increases* (*decreases*) *the net buy pressure*.

The cumulative change of the pending ask and bid volume during the last 30 minutes is an important indicator for general movements and possible imbalances in the market. However, following the logic above, given the slope of the ask curve and the change in the bid volume, a positive net ask order flow has no impact on the average upper tail expectations. Nevertheless, it improves investors' terms of trade and thus increases the net buy pressure. In contrast, in the setting by Parlour (1998), a positive order flow reduces the execution probabilities of limit orders and thus implies a crowding out effect. Consequently, we would expect a reduction in the net buy pressure. Following the latter argument leads to Hypothesis H7:

*H*7: *Net order flow*
A positive (*negative*) *net order flow during the last* 30 *min*, *given the ask and bid slope*, *decreases* (*increases*) *the net buy pressure*.

Observing past market periods makes it possible not only to identify potential trends in market participants' expectations but also to assess the uncertainty in the market. If the market reveals high uncertainty about the full information liquidation value of the asset, the informational content of the order book is expected to be diluted. As proxies for uncertainty in the market we use the midquote volatility as well as the order flow volatility as measured by the cumulative squared (demeaned) midquote changes and, respectively, cumulative squared (demeaned) signed order flow changes during the last 30 min. Foucault (1999) shows that a high volatility leads to higher spreads since liquidity suppliers face a higher picking-off risk. Consequently, the intensity of market order trading declines whereas the intensity of limit order trading increases.[11] However, given the bid-ask spread we expect a converse relation. Actually, both a high midquote volatility and order flow volatility indicate a high difference in expectations and valuations among traders. Ceteris paribus, differences in opinion should create active market order trading without implying a clear signal for the net buy pressure. Therefore, we expect that a high midquote and order flow volatility affect both the buy and sell intensity positively; however, they do not have any consistent impact on the net buy pressure.

*H*8: *Midquote and order flow volatility*
A high midquote and order flow volatility increase both the buy and sell intensity; *however*, *they do not have a systematic effect on the net buy pressure*.

[11] Since we do not model the limit order process, this hypothesis is not directly testable in the given framework. In this context, see for example Hall and Hautsch (2006).

4. Modelling the buy and sell intensity

Let t denote the calendar time and define $t_1^0, t_2^0, \ldots, t_{n^0}^0$ as the sequence of times when the order book changes due to the arrival of a market order, a new limit order or an amendment or cancellation of a pending limit order. Furthermore, let $t_1, t_2, \ldots, t_n$ denote the arrival times of market orders and $t_1^B, t_2^B, \ldots$ and $t_1^S, t_2^S, \ldots$ be the arrival times of buy (B) and sell (S) market orders, respectively.

Furthermore, let $N^0(t) = \sum_{i\geqslant 1} \mathbb{1}_{\{t_i^0 \leqslant t\}}$ represent the (right-continuous) counting function which counts changes in the order book occurring before and including time t. Correspondingly, $N^k(t) = \sum_{i\geqslant 1} \mathbb{1}_{\{t_i^k \leqslant t\}}$ counts all buy ($k = B$) or sell ($k = S$) market orders, respectively, occurring up to t. Then, the intensity function with respect to buy and sell order arrivals is given by

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

where $\mathscr{F}_t$ denotes the information set up to t. The intensity $\lambda^k(t; \mathscr{F}_t)$ is a positive process with left-continuous sample paths. Intuitively, the intensity function corresponds to the conditional probability per unit time of observing the arrival of a buy or sell market order in the *next* instant, given the current conditioning information such as the current state of the limit order book. It is the counterpart to the hazard function which is a central concept in traditional (discrete-time) duration analysis (see, for example, Kiefer, 1988).[12]

Russell (1999) proposes parameterizing the bivariate buy and sell intensity function

$$\lambda(t; \mathscr{F}_t) = \left(\lambda^B(t; \mathscr{F}_t), \lambda^S(t; \mathscr{F}_t)\right)' \tag{2}$$

in terms of the so-called autoregressive conditional intensity (ACI) model as given by

$$\lambda^k(t; \mathscr{F}_t) = \Psi^k(t) \lambda_0^k(t) s^k(t), \quad k \in \{B, S\}, \tag{3}$$

where $\Psi^k(t)$ is a function capturing the dynamics of the process, $\lambda_0^k(t)$ denotes a baseline component that specifies how the intensity evolves between two consecutive trades, and $s^k(t)$ captures a deterministic intraday seasonality pattern.

Let $z_1, z_2, \ldots, z_{n^0}$ be the sequence of market characteristics evaluated at the arrival times t_i^0. These variables are time-varying covariates reflecting any change of the order book occurring between consecutive transactions. In the following denote $M(t) = \sum_{i\geqslant 1} \mathbb{1}_{\{t_i < t\}}$ as the left-continuous counting function that counts all transactions that occurred *before* t. Accordingly, $M^0(t) = \sum_{i\geqslant 1} \mathbb{1}_{\{t_i^0 < t\}}$ counts all order book changes before t.

In order to ensure positivity of the intensity function, Russell (1999) proposes a specification of the dynamic intensity component $\Psi^k(t)$ as a log linear function given by

$$\ln \Psi^k(t) = \tilde{\Psi}^k_{M(t)+1} + z'_{M^0(t)} \gamma^k, \tag{4}$$

where γ^k with $k \in \{B, S\}$ is the coefficient vector associated with the explanatory variables $z_{M^0(t)}$. Note that $z_{M^0(t)}$ is updated whenever the limit order book changes, whereas $\tilde{\Psi}^k_{M(t)+1}$ is updated only when a new trade occurs. This specification implies that the function $\Psi^k(t)$

[12]The hazard function is typically applied in cross-sectional duration analysis, where it is defined as the instantaneous arrival rate given the time elapsed since the beginning of the spell and predetermined variables.

depends on order book information which is observable at least instantaneously *before* t. As a result, $\lambda^B(t;\mathscr{F}_t)$ and $\lambda^S(t;\mathscr{F}_t)$ depend on the state of the market observable instantaneously *before* t. Fig. 2 illustrates the dynamic behavior of the individual process components graphically.

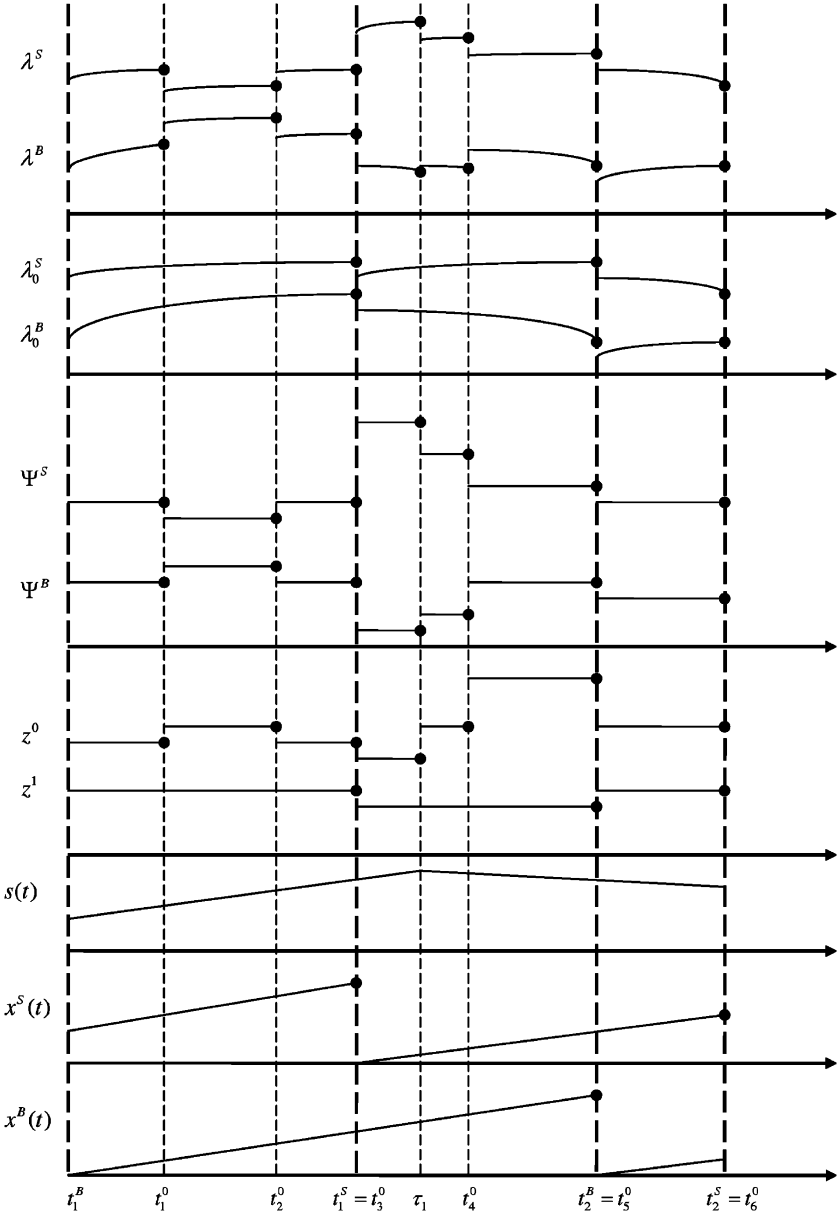

Fig. 2. Graphical illustration of the ACI components. Stylized patterns of the ACI components over a set of arrival points. The dots indicate the left-continuity of the processes. z^0 denote covariates which are updated at *any* point. z^1 denote covariates which are only updated whenever a trade arrives.

The (2×1) vector $\tilde{\Psi}_i := (\tilde{\Psi}_i^B, \tilde{\Psi}_i^S)'$ is parameterized in terms of a VARMA type specification, given by[13]

$$\tilde{\Psi}_i = \sum_{k \in \{B,S\}} (A^k \varepsilon_{i-1} + B\tilde{\Psi}_{i-1}) y_{i-1}^k, \tag{5}$$

where i indexes all trade arrivals $t_1, t_2, \ldots, \varepsilon_i$ is a (scalar) innovation term, $A^k = \{\alpha_j^k\}$ denotes a (2×1) vector of corresponding innovation parameters, and $B = \{\beta_{ij}\}$ is a (2×2) matrix of persistence parameters. Furthermore, y_i^k defines an indicator variable that takes the value one if the ith transaction is a buy ($k = B$) or a sell ($k = S$) and zero otherwise.

The innovation term ε_i is computed as

$$\varepsilon_i = \sum_{k \in \{B,S\}} (1 - \Lambda^k(t_{N^k(t_i)-1}^k, t_{N^k(t_i)}^k)) y_i^k, \tag{6}$$

where

$$\Lambda^k(t_{N^k(t_i)-1}^k, t_{N^k(t_i)}^k) := \int_{t_{N^k(t_i)-1}^k}^{t_{N^k(t_i)}^k} \lambda^k(s; \mathscr{F}_s)\, \mathrm{d}s : \quad k \in \{B, S\} \tag{7}$$

denotes the integral over the buy and sell intensity function computed from the previous to the most current trade arrival time of process k. Under the assumption that the process is orderly, so that only one transaction can occur at any instant,[14] the innovation ε_i is a scalar random variable which is computed from the integrated intensity function associated with the most recently observed process. However, note that the impact of the innovation term on the buy and sell intensity differs as long as $A^B \neq A^S$.[15] A well known result in the statistics literature is that under fairly weak assumptions the integrated intensity function follows an i.i.d. standard exponential process, thus $\Lambda^k(t_{i-1}^k, t_i^k) \sim$ i.i.d. Exp(1).[16] Therefore, under correct model specification, ε_i is a mixture of exponential variables implying that the stationarity conditions for $\tilde{\Psi}_i$ depend solely on the eigenvalues of B. In particular, the process $\tilde{\Psi}_i$ is weakly stationary if the eigenvalues of B lie inside the unit circle. Note that the function $\Psi^k(t)$ changes instantaneously after the arrival of each market or limit order and remains constant until (and inclusive of) the next order arrival (see Fig. 2). However, the evolution of the buy and sell intensity, as a deterministic function of time between consecutive order arrivals, is captured by the baseline intensity function $\lambda_0^k(t)$ which is specified as a product of Burr hazard functions. In this case $\lambda_0^k(t)$ is given by

$$\lambda_0^k(t) = \exp(\omega^k) \prod_{r \in \{B,S\}} \frac{x^r(t)^{p_r^k - 1}}{1 + \kappa_r^k x^r(t)^{p_r^k}}, \quad (p_r^k > 0,\ \kappa_r^k \geqslant 0); \quad k \in \{B, S\}, \tag{8}$$

where ω^k, p_r^k and κ_r^k are parameters to be estimated while $x^r(t)$ denotes the time elapsed since the arrival of the last event of type r before t. According to specification (8), the buy

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

[14]In our empirical application the market structure ensures that this assumption is fulfilled.

[15]Russell (1999) proposed allowing the persistence matrix B to also depend on the type of the most recent event. However, since it is difficult to establish the stationarity conditions for such a regime-switching process, we retain specification (5).

[16]See Theorem 1 in Brown and Nair (1988) or the discussion in Bowsher (2007).

(sell) intensity at any point t is not only driven by the time elapsed since the last buy (sell) trade but also by the time elapsed since the last sell (buy) transaction.

The seasonality functions, $s^k(t)$, are parameterized as linear spline functions which are normalized to one at the beginning of the trading day in order to ensure that the constants ω^k are identified. Hence, by denoting $\tau_j, j = 1\ldots, S$ as S nodes during a trading day and v_j^k as the corresponding seasonality parameters to be estimated, $s^k(t)$ is given by

$$s^k(t) = 1 + \sum_{j=1}^{S} v_j^k(t - \tau_j) \cdot \mathbb{1}_{\{t>\tau_j\}}. \tag{9}$$

Karr (1991) shows that a statistical model can be completely specified in terms of the intensity function. Hence, by denoting the vector of all model parameters by θ, the log likelihood function of the bivariate ACI model is obtained as

$$\ln \mathscr{L}(\theta) = \sum_{k=\{B,S\}} \sum_{i=1}^{n} \{-\Lambda^k(t_{i-1}, t_i) + y_i^k \ln \lambda^k(t_i; \mathscr{F}_{t_i})\}. \tag{10}$$

Given correct specification of the model, the residuals $\hat{\Lambda}_i^k := \hat{\Lambda}^k(t_i^k, t_{i-1}^k)$ should be distributed as i.i.d. unit exponential random variables. As a result, model evaluation can be performed by testing the dynamic properties of the residual series, using for example Ljung–Box statistics, and by testing its distribution properties. For instance, Engle and Russell (1998) propose a test against excess dispersion based on the asymptotically normal test statistic $\sqrt{n^k/8}(\hat{\sigma}^2_{\Lambda^k} - 1)$, where $\hat{\sigma}^2_{\Lambda^k}$ is the empirical variance of the residual series with $k \in \{B, S\}$.

On the basis of the buy and sell intensities $\lambda^B(t; \mathscr{F}_t)$ and $\lambda^S(t; \mathscr{F}_t)$, we define the so-called *net buy pressure* formally as

$$\Delta^B(t) := \ln \lambda^B(t; \mathscr{F}_t) - \ln \lambda^S(t; \mathscr{F}_t). \tag{11}$$

Then, by exploiting the log-linear structure of the ACI model, the marginal change of $\Delta^B(t)$ induced by a change of $z_{M^0(t)}$ is easily computed as

$$\frac{\partial \Delta^B(t)}{\partial z_{M^0(t)}} = \gamma^B - \gamma^S. \tag{12}$$

As illustrated in Section 6, this expression allows us to draw straightforward statistical inference regarding the influence of changes in the state of the market on the net buy pressure.

5. The data

The data extracted from the SEATS system provides information about the complete order flow during normal trading periods as well as the opening and closing auctions. By accounting for any changes of the order book in pre-trading, trading and after-trading periods, we are able to reconstruct the complete order book at any point in time. The empirical analysis is based on the five most liquid stocks during the trading period July and August 2002: The National Australian Bank (NAB), a banking and financial services company; BHP Billiton Limited (BHP), a large diversified resource company; Mount Isa Mines Limited (MIM), a base metal mining company; Telstra (TLS), a telecommunications and information services company; and Woolworths (WOW), a retail company.

The sample period covers the 45 trading days between July 8th and August 30th, 2002. Data from the opening and closing call auctions periods are not utilized and all crossings and off market trades have been removed. Moreover, since we construct covariates reflecting the market activities during the most recent 30 min, we do not model the buy and sell processes between 10:00 and 10:30. This data adjustment also removes the potential influence of specific post-opening effects.

Table 2 presents the basic summary statistics of the order arrival processes for all stocks considered in this study.[17] Across all stocks the number of limit orders exceeds the number of market orders. This is particularly evident for MIM, where the ratio of limit orders to market orders is nearly three to one. Overall we observe more buy trades than sell trades and more bid limit orders than ask limit orders which may be associated with an upward market trend during the sample period. We observe that around 10% of all order book changes are due to cancellations of pending orders. As indicated by the highly significant Ljung–Box statistics of the durations between order submissions, trade and limit order arrival rates are positively autocorrelated and reveal strong persistence. This property of the processes necessitates the use of a dynamic intensity model as discussed in Section 4.

In order to test the economic hypotheses formulated in Section 3, we generate four groups of explanatory variables. Table 3 gives a precise definition of the individual covariates. The first type of variable captures characteristics of overnight returns. 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, 2007). In order to control for such effects, we include the log ratio between the previous day's closing price and the current opening price as regressor (OCP). The interaction with two time dummies ($OCP1$ and $OCP2$) allows us to investigate whether the influence of overnight returns changes over a trading day. The second category contains variables that are observed only when a market order is executed. Here, we include the difference between the posted log limit price and the prevailing log ask price in case of a buy or log bid price in case of a sell (DQP) as a measure for the investor's implicit marginal valuation (see Hypothesis H1). Moreover, we compute the change of the best ask/bid log quote due to a transaction (DP).[18] In order to control for potential non-linearities, we interact DP also with a dummy variable indicating whenever best ask and bid prices are shifted by more than one tick ($DP1$). Hypothesis H2 is tested by including the signed log traded quantity at the most recent transaction (TRV) and its interaction with a dummy variable indicating volumes greater than the median volume ($TRV1$). Moreover, we also compute the signed difference between the quoted and the traded log volume as a measure for the non-executed quantity of a market order (DV). The third group of variables captures the most recent state of the order book as well as the characteristics of the most recent limit order arrivals. Hypothesis H3 is analyzed by including the signed log volume of a limit order set below (above), at or above (below) the most current best ask (bid) price (LO_{-1}, LO_0, LO_{+1}). Correspondingly, we record the signed log volume of a cancellation above or below the current best ask/bid ($CAN0$, $CAN1$). To test Hypothesis H4, we compute the relative price differential between limit prices associated with specific volume quantiles (relative to the current mid-quote price). These variables capture the piecewise slopes of the ask and bid curves evaluated at the

[17]The summary statistics are computed including the trading period between 10:00 and 10:30.

[18]Note that the trading rules guarantee that DQP and DP are positive only for buys and negative only for sells.

Table 3
Explanatory variables
This table provides the definition of the explanatory variables used in the empirical study.

Variables that are constant during a trading day	
OCP	Difference between the current opening log price and the previous days' closing log price
$OCP1$	OCP interacted with a dummy variable indicating a time of day before 1:00
$OCP2$	OCP interacted with a dummy variable indicating a time of day after 1:00
Variables associated with most recent trade	
DQP	Difference between the posted limit log price and the current best log ask (bid) price for buys (for sells)
DP	log return of the best ask quote (due to a buy) or best bid quote (due to a sell), respectively
$DP1$	DP interacted with a dummy variable indicating ask/bid changes by more than one tick
TRV	log transaction volume (positive for buys, negative for sells)
$TRV1$	TRV interacted with a dummy variable for volumes greater than the median volume
DV	difference between the log quoted volume and log traded volume (positive for buys, negative for sells)
Variables observed at the last arriving order	
LO_{-1}	log volume of a limit order set below (above) the current ask (bid), positive for asks, negative for bids
LO_0	log volume of a limit order set at the current ask or bid, positive for asks, negative for bids
LO_{+1}	log volume of a limit order set above (below) the current ask (bid), positive for asks, negative for bids
$CAN0$	log volume of a cancelled order below (above) or at the best ask (bid), positive for asks, negative for bids
$CAN1$	log volume of a cancelled order above (below) or at the best ask (bid), positive for asks, negative for bids
A_x	Limit price associated with the x%-quantile of the cumulated volume on the ask queue
B_x	Limit price associated with the x%-quantile of the cumulated volume on the bid queue
MQ	$(A_0 + B_0)/2$
$ASL02$	$ASL02 = (A_{02} - A_0)/(MQ \cdot 2)$
$ASL05$	$ASL05 = (A_{05} - A_{02})/(MQ \cdot 3)$
$ASL10$	$ASL10 = (A_{10} - A_{05})/(MQ \cdot 5)$
$ASL20$	$ASL20 = (A_{20} - A_{10})/(MQ \cdot 10)$
$ASL50$	$ASL50 = (A_{50} - A_{20})/(MQ \cdot 30)$
$ASL90$	$ASL90 = (A_{90} - A_{50})/(MQ \cdot 40)$
$BSL02$	$BSL02 = (B_0 - B_{02})/(MQ \cdot 2)$
$BSL05$	$BSL05 = (B_{02} - B_{05})/(MQ \cdot 3)$
$BSL10$	$BSL10 = (B_{05} - B_{10})/(MQ \cdot 5)$
$BSL20$	$BSL20 = (B_{10} - B_{20})/(MQ \cdot 10)$
$BSL50$	$BSL50 = (B_{20} - B_{50})/(MQ \cdot 30)$
$BSL90$	$BSL90 = (B_{50} - B_{90})/(MQ \cdot 40)$
AV	log pending volume on the ask queue
BV	log pending volume on the bid queue
$\overline{ASL05}$	$(A_{05} - A_0)/(MQ \cdot 5)$
$\overline{BSL05}$	$(B_{05} - B_0)/(MQ \cdot 5)$
SPR	$(A_0 - B_0)/MQ$

Table 3 (*continued*)

Variables observed during the last 30 min	
OFL	Cumulated signed log ask order flow
DMQ	Log midquote return
DASL	Change of $\overline{ASL05}$
DBSL	Change of $\overline{BSL05}$
VOLA	Square root of cumulated squared demeaned log midquote changes
OFLV	Square root of cumulated squared demeaned differences between log pending ask and bid volumes

individual volume quantiles ($ASL\cdot$, $BSL\cdot$). Moreover, we include the log aggregated trading volume on the bid and ask queues (AV and BV). 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 these variables reflect the overall current aggregated demand and supply in the market. Furthermore, as a measure for the tightness of the market and to test Hypothesis H5, we compute the relative spread between the current best bid and best ask price (SPR) relative to the midquote. The fourth group of variables are indicators for market movements during the last 30 min. Hypotheses H6 and H7 are evaluated by computing the signed order flow as the cumulated change of the pending log ask volume in excess of the log bid volume during the last 30 min (OFL) and the corresponding log midquote return (DMQ). Moreover, we record the changes of the ask and bid slopes during the last 30 min. In order to restrict the number of covariates, we focus only on the shape of the ask and bid curves close to the midquote ($DASL$ and $DBSL$). Finally, testing Hypothesis H8 requires us to generate variables reflecting the uncertainty in the market. In this context, we compute the order flow volatility by the square root of the cumulated squared differences between the pending log ask and bid volume ($OFLV$). The ask-bid differences are demeaned by the average difference between the pending log ask and bid volume during the last 30 min. Finally, we record the midquote volatility by the square root of the cumulated squared demeaned log midquote changes during the last 30 min ($VOLA$).

Figs. 3–5 show intraday plots of various order book variables based on linear spline regressions using one hour knots for the stocks BHP, NAB and TLS.[19] We observe clear patterns which are mainly driven by opening, lunchtime and closing effects. It is evident that the proportion of market orders clearly increases before market closure indicating that traders tend to close their positions overnight. Overall we find a higher arrival rate of aggressive orders as well as cancellations after market opening which declines around noon, increases in the afternoon and declines again before market closure. Quite similar intraday patterns are found for the bid-ask spread and the depth in the lower section of the order queues. In accordance with predictions from market microstructure theory, we observe the highest spreads and lowest depth after market opening where overnight information is processed and uncertainty is still high. For trading volumes we find the well known U-shape pattern indicating large volumes after opening and before closure and a significant dip in the middle of the trading day. In contrast, the standing volume in the

[19]For sake of brevity we do not show the plots associated with the other stocks since they look similar.

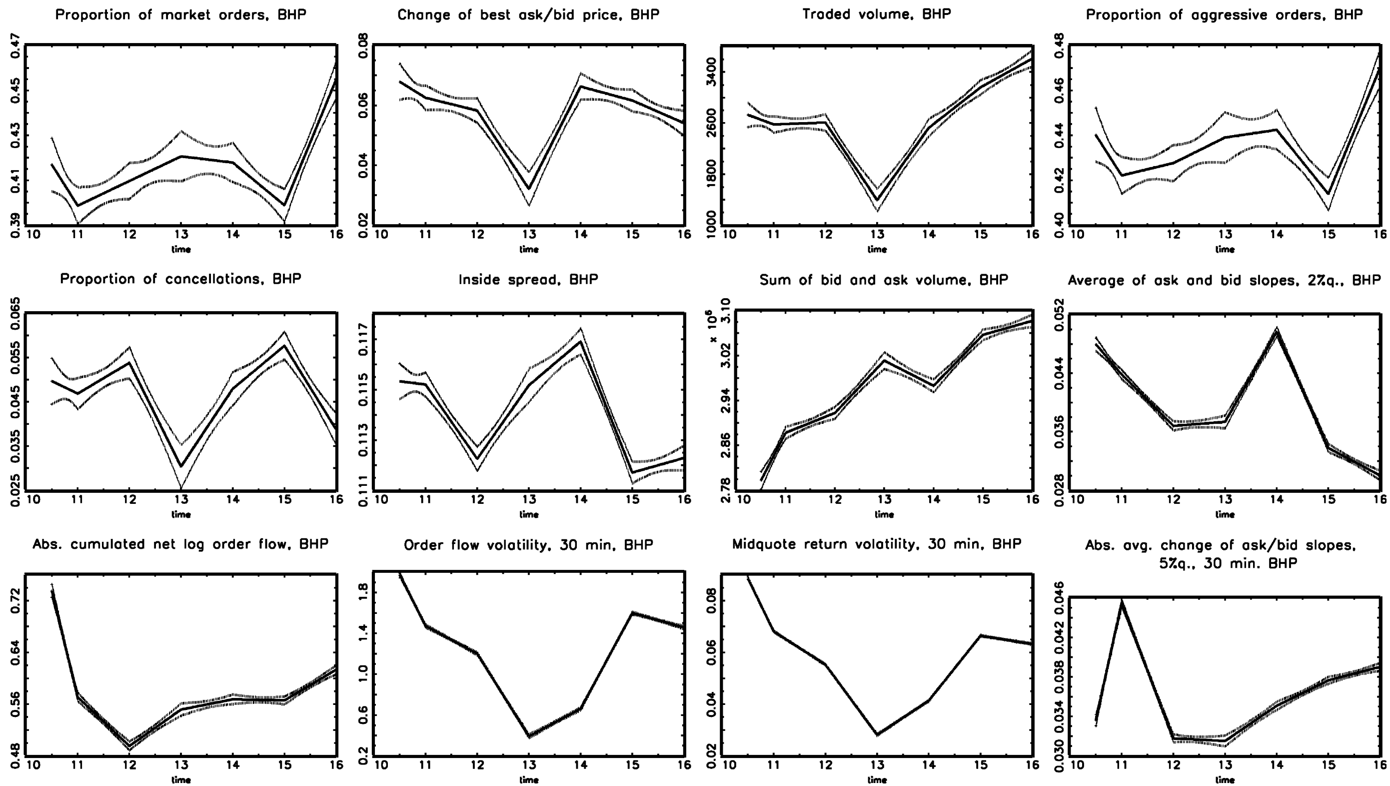

Fig. 3. Intraday seasonality functions of different order book variables for the BHP stock. Seasonality functions estimated based on linear spline regressions using one hour nodes. The dotted lines show the 5% significance confidence bands. Top row, from left to right: proportion of market vs. limit orders, changes of best ask/bid prices due to a trade, transaction volume, proportion of limit orders within the 1% quantile. Second row: proportion of cancellations, relative bid-ask spread, cumulated standing volume on both sides of the market, average bid and ask slopes with respect to the 2% volume quantile. Third row: absolute cumulated net log order flow, order flow volatility, midquote return volatility and absolute average changes of the bid and ask slopes with respect to the 5% volume quantile.

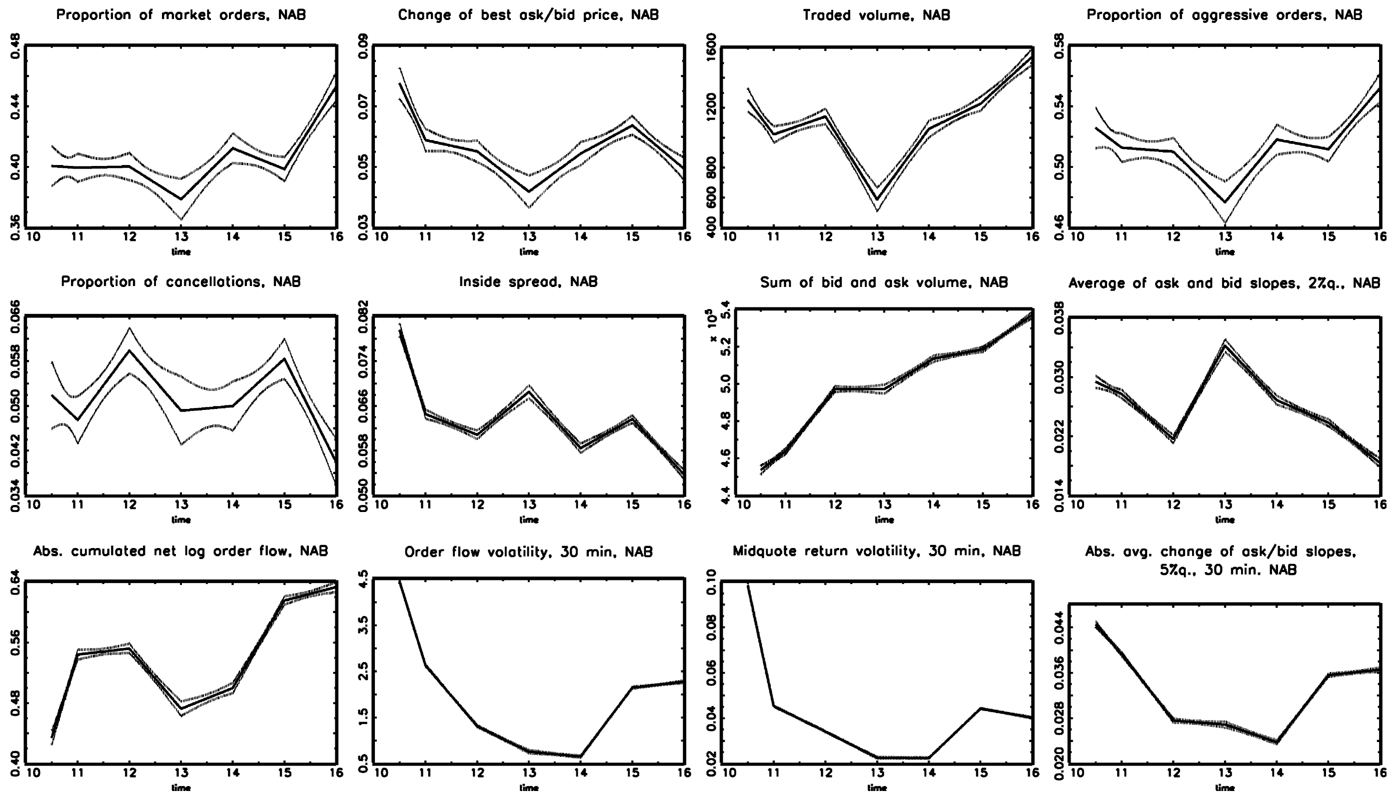

Fig. 4. Intraday seasonality functions of different order book variables for the NAB stock. Seasonality functions estimated based on linear spline regressions using one hour nodes. The dotted lines show the 5% significance confidence bands. Top row, from left to right: proportion of market vs. limit orders, changes of best ask/bid prices due to a trade, transaction volume, proportion of limit orders within the 1% quantile. Second row: proportion of cancellations, relative bid-ask spread, cumulated standing volume on both sides of the market, average bid and ask slopes with respect to the 2% volume quantile. Third row: absolute cumulated net log order flow, order flow volatility, midquote return volatility and absolute average changes of the bid and ask slopes with respect to the 5% volume quantile.

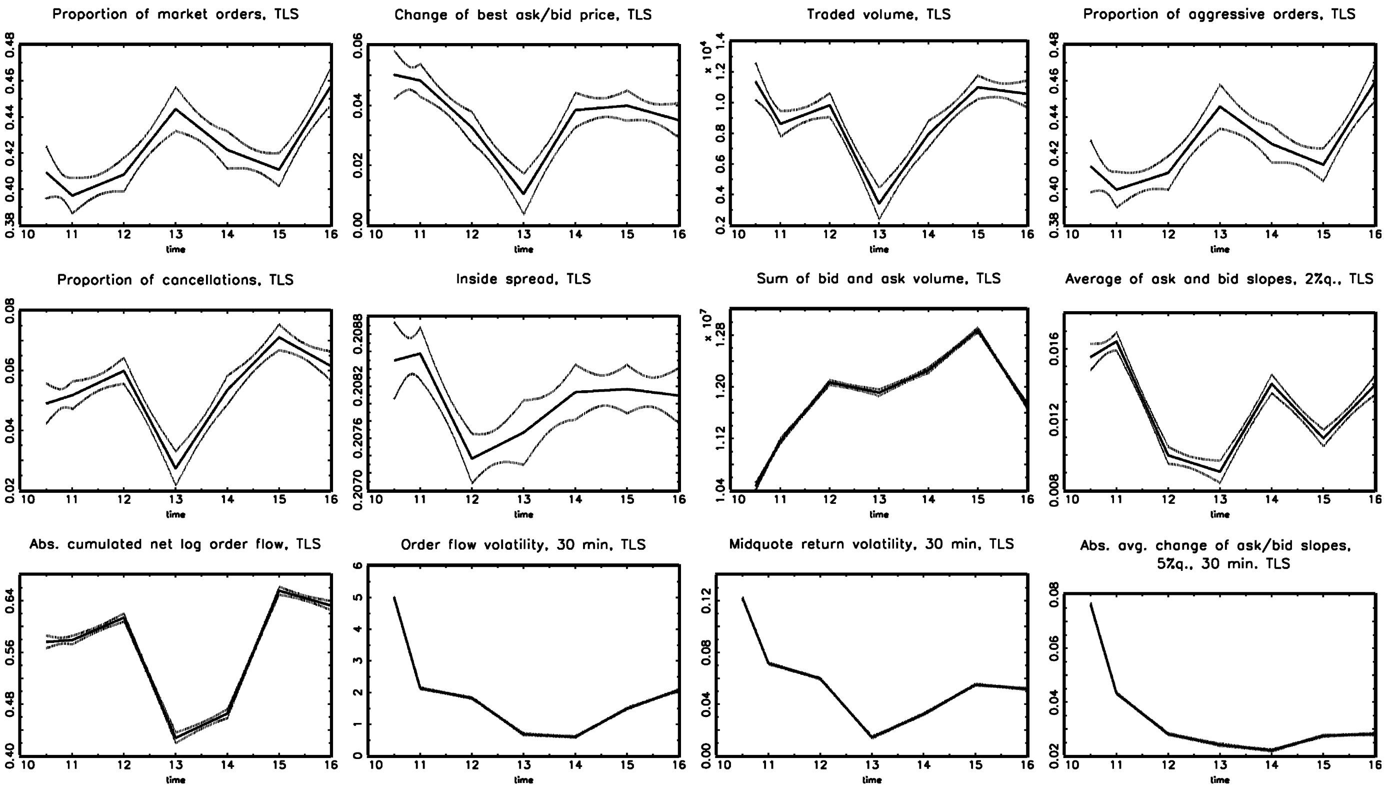

Fig. 5. Intraday seasonality functions of different order book variables for the TLS stock. Seasonality functions estimated based on linear spline regressions using one hour nodes. The dotted lines show the 5% significance confidence bands. Top row, from left to right: proportion of market vs. limit orders, changes of best ask/bid prices due to a trade, transaction volume, proportion of limit orders within the 1% quantile. Second row: proportion of cancellations, relative bid-ask spread, cumulated standing volume on both sides of the market, average bid and ask slopes with respect to the 2% volume quantile. Third row: absolute cumulated net log order flow, order flow volatility, midquote return volatility and absolute average changes of the bid and ask slopes with respect to the 5% volume quantile.

order queues reveals a systematic increase during the morning and a slight decline in the afternoon.[20]

6. Empirical results

6.1. Statistical properties of the buy/sell intensity

For each stock, we estimate three different model specifications. Table 4 reports the estimates based on a model where the explanatory variables are updated at each *trade* arrival. In this setting, the vector z_i captures the state of the market instantaneously *before* the arrival of a transaction at t_i whereas any limit order arrivals and thus changes of the limit order book between sequential trades are ignored.[21] Table 5 presents the estimates for a more general specification based on (time-varying) covariates which are updated whenever the order book is changed due to the arrival of new orders or changes in pending orders.[22] Moreover, we estimate an intensity specification without any covariates.[23] For all stocks, it turns out that the inclusion of covariates leads not only to a significantly better Bayes Information Criterion (BIC), but also to improved residual diagnostics. This illustrates that order book information has substantial explanatory power for the buy and sell intensity in the market.

All regressors are weakly exogenous for the intensity function as they enter the model in lagged form (recall Eq. (4)). The lag order of each model is chosen using the BIC leading to an ACI(1,1) parameterization as the preferred specification for all models. Furthermore, the best goodness-of-fit in terms of the BIC is found for parsimonious specifications which exclude spill-over effects in the baseline function, i.e., where $p_B^S = p_S^B = 1$ and $\kappa_B^S = \kappa_S^B = 0$. Moreover, since the intraday patterns of buy and sell arrivals are very similar, the most parsimonious model is obtained by specifying a common seasonality function for both processes. According to Eq. (9), we specify the seasonality function as a linear spline function based on 6 equally-spaced nodes between 10:30 and 16:00. Fig. 6 shows the estimated intraday patterns for all five stocks. These functions reveal the typical U-shape pattern which is well documented in the empirical literature on intraday data.

The best goodness-of-fit in terms of the BIC is revealed for the specification shown in Table 5 which indicates the importance of accounting for the limit order arrival process between individual transactions. For all stocks, we observe strong persistence in the intensity processes as indicated by the relatively small innovation coefficients and the persistence parameters which are close to the non-stationary region.[24] There is also empirical evidence for significant, and in most cases positive, interdependences 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. The residual diagnostics in the Tables 4 and 5 show that the specifications broadly capture the dynamics in the data, as revealed by the relatively low values of the Ljung–Box statistics. Nevertheless, because of the large number of observations, in around half of all cases the

[20] However, for NAB and BHP, we find a clear increasing trend over the whole trading day.

[21] In Fig. 2, this type of covariates is represented by the variable z^1.

[22] In Fig. 2, this type of covariates is represented by the variable z^0.

[23] For sake of brevity the corresponding estimates are not shown here. They are available upon request from the authors.

[24] Nevertheless, in all specifications the eigenvalues of the persistence matrix B are less than unity.

Table 4
Estimates of ACI models with covariates evaluated at each transaction

This table gives the maximum likelihood estimates of a bivariate ACI(1,1) model for the buy (B) and sell (S) intensity, $\lambda^k(t;\mathscr{F}_t) = \lim_{h\downarrow 0}\frac{1}{h}\Pr[(N^k(t+h)-N^k(t))>0|\mathscr{F}_t]$, $k\in\{B,S\}$, where $\mathscr{F}_t$ denotes the information set up to calendar time t, $N^k(t)=\sum_{i\geqslant 1}\mathbb{1}_{\{t_i^k\leqslant t\}}$ denotes the right-continuous counting function and t_i^k the arrival time of the ith trade of type k. The intensity processes are modelled as $\lambda^k(t;\mathscr{F}_t)=\Psi^k(t)\lambda_0^k(t)s(t),\ k\in\{B,S\}$, where $\Psi^k(t)=\exp(\tilde{\Psi}^k_{M(t)+1}+z'_{M(t)}\gamma^k)$, $\tilde{\Psi}^k_{M(t)+1}$ is a dynamic function, $M(t)=\sum_{i\geqslant 1}\mathbb{1}_{\{t_i<t\}}$ denotes the left-continuous counting function based on the arrival times of trades, t_i, z_i denotes a vector of market characteristics observed at t_i and γ^k is the corresponding coefficient vector. $\lambda_0^k(t)=\exp(\omega^k)(x^k(t)^{p^k-1})/(1+\kappa^k x^k(t)^{p^k})$, where $x^k(t)$ denotes the time elapsed since the arrival of the last buy/sell before t, and ω^k, p^k and κ^k are parameters to be estimated. $s(t)$ denotes a seasonal spline function with $s(t)=1+\sum_{j=1}^S v_j(t-\tau_j)\cdot\mathbb{1}_{\{t>\tau_j\}}$, where τ_j, $j=1\ldots,S$ denote S nodes during a trading day and v_j are seasonality coefficients to be estimated. By indexing the sequence of transactions by i, the (2×1) vector $\tilde{\Psi}'_i=(\tilde{\Psi}^B_i,\tilde{\Psi}^S_i)$ is specified by $\tilde{\Psi}_i=\sum_{k\in\{B,S\}}(A^k\varepsilon_{i-1}+B\tilde{\Psi}_{i-1})y^k_{i-1}$ with $A^k=\{\alpha_j^k\}$ denoting a (2×1) vector and $B=\{\beta_{ij}\}$ a (2×2) matrix of parameters, and y_i^k defining an indicator variable that takes the value 1 if the ith transaction is of type k. The innovation ε_i is given by $\varepsilon_i=\sum_{k\in\{B,S\}}(1-\Lambda^k(t^k_{N^k(t_i)-1},t^k_{N^k(t_i)}))y_i^k$, where $\Lambda^k(t^k_{i-1},t^k_i):=\int_{t^k_{i-1}}^{t^k_i}\lambda^k(s;\mathscr{F}_s)\,\mathrm{d}s$. The sample contains all market orders of the NAB, BHP, MIM, TLS and WOW stock during the period July 8th to August 30th 2002. Standard errors are computed based on the outer product of gradients. The time scale is standardized by the average duration between two trades. The time series are re-initialized at each trading day.

Ask side						Bid side					
	NAB	BHP	MIM	TLS	WOW		NAB	BHP	MIM	TLS	WOW
ACI parameters											
ω^B	0.06	−0.24*	0.31*	−0.16	−0.04	ω^S	0.10	−0.49***	−0.05	−0.42***	−0.19
p^B_B	0.88***	0.87***	0.85***	0.88***	0.85***	p^S_S	0.89***	0.83***	0.84***	0.88***	0.83***
κ^B_B	0.09***	0.00	0.00	0.00	0.00	κ^S_S	0.10***	0.00	0.00	0.00	0.00
α^B_B	0.11***	0.05***	0.13***	0.10***	0.05***	α^B_S	0.04***	0.01***	−0.01	−0.03***	0.02***
α^S_B	0.04***	0.01*	−0.01	−0.02***	0.01*	α^S_S	0.08***	0.07***	0.14***	0.06***	0.09***
β_{BB}	0.86***	0.96***	0.95***	0.94***	0.99***	β_{SB}	0.02**	0.01***	0.00	0.06***	0.01*
β_{BS}	−0.02**	0.01***	0.00	0.04***	0.04***	β_{SS}	0.95***	0.97***	0.93***	0.96***	0.94***
Impact of overnight price changes											
$OCP1$	−1.67	0.15	0.42	1.52	2.22	$OCP1$	1.75	0.10	0.65	0.89	−4.63*
$OCP2$	−1.82*	0.10	0.15	1.69	2.17	$OCP2$	1.49	−0.08	0.01	0.79	−4.87*

Impact of the most recent transaction											
DQP	−0.04	0.01	−0.02	0.00	0.09*	*DQP*	0.17*	0.06*	0.03	0.00	−0.03
DP	−16.00***	−6.34***	−0.80***	−3.22***	−6.04***	*DP*	14.28***	8.04***	0.92***	3.09***	7.53***
*DP*1	8.41***	2.27***	0.75	0.72	2.71***	*DP*1	−7.07***	−1.03*	−0.12	−0.86	−3.80***
TRV	0.13***	0.04***	0.10***	−0.01	0.10***	*TRV*	−0.12***	−0.15***	−0.07**	0.00	−0.25***
*TRV*1	0.08***	0.13***	0.07**	0.15***	0.09***	*TRV*1	−0.05**	−0.11***	−0.15***	−0.17***	0.01
DV	−0.17**	0.44***	0.73	0.93***	−0.13	*DV*	0.34***	−0.19**	−0.56	0.20	0.09
Impact of the current state of the market											
AV	1.38	−1.05	−0.23	−1.22	3.44	*AV*	0.38	0.39	−0.45	−0.18	6.85***
BV	−0.15	0.73	0.33	−1.00	−4.34***	*BV*	−1.51	−0.99	−0.02	−1.98	−3.44**
*BSL*02	−3.04***	−3.31***	−1.22***	−4.70***	−1.26***	*BSL*02	1.06***	3.55***	2.43***	6.77***	0.64***
*ASL*02	1.75***	2.95***	1.64***	6.51***	1.19***	*ASL*02	−0.50**	−2.66***	−0.24	−3.45***	−0.19
*BSL*05	−1.05***	−0.50**	−1.81***	−3.58***	−1.15***	*BSL*05	1.21***	0.84***	3.08***	3.78***	0.18
*ASL*05	1.06***	0.59**	1.04***	5.11***	0.76***	*ASL*05	−0.08	−0.08	−0.08	−2.53***	0.17
*BSL*10	0.15	−0.14	−1.85***	−1.29***	−0.40*	*BSL*10	0.42*	−0.13	2.21***	2.14***	0.38*
*ASL*10	0.05	−0.04	0.90***	3.15***	−0.38*	*ASL*10	0.35	0.28	−0.61**	−0.66*	−0.33
*BSL*20	0.23	−0.69***	−1.76***	1.41**	0.36	*BSL*20	0.24	0.32	1.30***	0.40	0.33
*ASL*20	0.55**	−0.23	−0.32	0.49	−0.20	*ASL*20	0.12	−0.24	−0.36	0.53	−0.21
*BSL*50	0.17	−0.81***	−1.83***	−0.62	0.75	*BSL*50	0.78***	0.57*	1.62**	0.62	0.32
*ASL*50	−0.05	0.07	0.16	0.49	0.43	*ASL*50	0.84*	−0.04	0.57**	−0.24	−1.00
*BSL*90	0.16	−0.77*	−0.96	−1.20	1.05	*BSL*90	−0.18	0.66	0.25	−0.11	0.75
*ASL*90	2.00***	1.01***	0.89*	−0.38	−1.15	*ASL*90	1.75**	0.89***	−0.66	0.02	−4.24***
SPR	−6.37***	−3.58***	−0.38	−0.46	−2.64***	*SPR*	−5.24***	−1.86***	0.38	0.13	−2.47***
Impact of the market activity during last 30 minutes											
VOLA	0.22	0.15	−0.06	0.23	−0.18	*VOLA*	0.08	0.04	−0.15	0.00	0.32
DMQ	−1.96	−4.17***	−3.22*	−3.34	−14.50***	*DMQ*	1.83	−0.75	0.82	1.64	−10.15***
DASL	−0.57*	0.22	0.09	0.31	−0.19	*DASL*	−0.59*	0.16	−1.40**	0.91**	−0.45
DBSL	1.62***	0.31	0.40	0.57	1.11***	*DBSL*	−0.52	0.00	−1.25*	−0.12	1.10***
OFL	−0.19	0.00	−0.02	−0.16	−0.48***	*OFL*	−0.23*	0.05	0.63	0.02	−0.24
OFLV	0.08***	0.06***	−0.03	0.00	0.04***	*OFLV*	0.06***	0.10***	0.00	0.02	0.06***

Table 4 (*continued*)

Ask side						Bid side					
	NAB	BHP	MIM	TLS	WOW		NAB	BHP	MIM	TLS	WOW
Seasonality parameters											
v_1	-1.50^{***}	-0.10	-1.76^{***}	-0.52	-1.88^{***}	v_4	1.33^{***}	2.14^{***}	0.70^{***}	2.83^{***}	0.65^{***}
v_2	1.54^{***}	-0.27	1.64^{***}	1.80^{***}	1.70^{***}	v_5	-0.24^{**}	-0.26	0.02	2.10^{*}	-0.03
v_3	-0.85^{***}	-0.94^{***}	-0.40^{**}	-2.50^{***}	-0.28^{**}	v_6	0.13	0.90^{***}	0.68^{***}	3.40	0.23^{**}
Diagnostics											
n	34,296	44,604	7,395	30,878	19,787						
LL	−51,357	−68,019	−10,115	−48,485	−26,625						
BIC	−51,775	−68,437	−10,467	−48,889	−27,011						
Residuals ask side						*Residuals sell side*					
Mean of $\hat{\Lambda}_i$	1.00	1.00	0.99	1.00	1.00		1.00	1.00	0.99	1.00	1.00
S.D. of $\hat{\Lambda}_i$	1.05	1.06	1.06	1.06	1.05		1.04	1.07	1.09	1.05	1.07
LB(20) of $\hat{\Lambda}_i$	49.95^{***}	26.89	15.13	26.12	43.31^{***}		36.04^{**}	19.51	12.53	48.44^{***}	25.74
Exc. disp.	4.36^{***}	7.31^{***}	2.94^{***}	5.33^{***}	3.52^{***}		4.14^{***}	7.18^{***}	3.46^{***}	4.02^{***}	5.04^{***}

Diagnostics: Log Likelihood (LL), Bayes information criterion (BIC) and diagnostics (mean, standard deviation, Ljung–Box statistic and excess dispersion test) of the ACI residuals $\hat{\Lambda}_i^k$, $k \in \{B, S\}$.

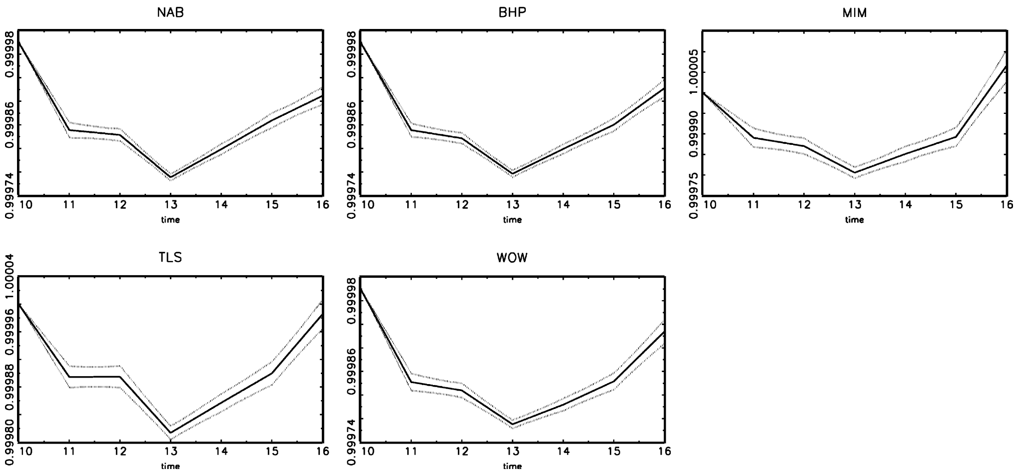

Fig. 6. Estimated intraday seasonality functions of the estimated trading intensity for the NAB, BHP, MIM, TLS and WOW stock. The estimates are based on an ACI specification without covariates (not shown in the paper) which includes the complete trading day.

null hypothesis of no correlation in the ACI residuals is still rejected. This is particularly true for NAB, BHP and TLS. As indicated by estimated parameter values for p_B^B and p_S^S being smaller than one, we find a negative duration dependence, i.e., the baseline intensity function decreases with the length of a spell. The residual diagnostics also report means and standard deviations of the ACI residuals close to one indicating that the assumed Burr specification widely captures the distributional properties of the data. Nevertheless, we still find evidence for a slight over-dispersion in the residuals, and as a consequence of the large sample sizes, the null hypothesis of no excess dispersion cannot be rejected in most cases.

6.2. Economic determinants of the net buy pressure: testing the economic hypotheses

We now summarize our findings regarding the impact of order book variables on both the buy and sell intensity and the resulting net buy pressure, $\Delta^B(t)$. As shown in Section 4, the marginal impact of the covariates on $\Delta^B(t)$ is measured as $\gamma^B - \gamma^S$. The corresponding estimates are reported in Table 6, where the standard errors are computed by applying the Delta method using the estimated covariance matrix of the parameter estimates as reported in Tables 4 and 5.

6.2.1. The impact of the most recent transaction

In nearly all specifications the variable *DQP* is found to be insignificant. The distance between the limit price set by an investor and the prevailing best ask or bid quote does not have a significant effect either on the buy and sell intensity or on the resulting net buy pressure. Hence, no confirmation of Hypothesis H1 (a) is found. In contrast, we observe highly significant reactions of the buy and sell intensity after a change of the best ask or bid quote. As revealed by the estimates of the coefficients associated with *DP* and *DP*1, the buy (sell) intensity is decreasing (increasing) after an upward (downward) movement of the

Table 5
Estimates of ACI models with covariates evaluated at each order arrival.

This table gives the maximum likelihood estimates of a bivariate ACI(1,1) model for the buy (B) and sell (S) intensity, $\lambda^k(t;\mathscr{F}_t) = \lim_{h\downarrow 0}\frac{1}{h}\Pr[(N^k(t+h)-N^k(t))>0|\mathscr{F}_t]$, $k\in\{B,S\}$, where $\mathscr{F}_t$ denotes the information set up to calendar time t, $N^k(t)=\sum_{i\geqslant 1}\mathbb{1}_{\{t_i^k\leqslant t\}}$ denotes the right-continuous counting function and t_i^k the arrival time of the i-th trade of type k. The intensity processes are modelled as $\lambda^k(t;\mathscr{F}_t)=\Psi^k(t)\lambda_0^k(t)s(t),\ k\in\{B,S\}$, where $\Psi^k(t)=\exp(\tilde{\Psi}^k_{M(t)+1}+z'_{M^0(t)}\gamma^k)$, $\tilde{\Psi}^k_{M(t)+1}$ is a dynamic function, $M(t)=\sum_{i\geqslant 1}\mathbb{1}_{\{t_i<t\}}$ denotes the left-continuous counting function based on the arrival times of trades, t_i, and $M^0(t)=\sum_{i\geqslant 1}\mathbb{1}_{\{t_i^0<t\}}$ denotes the left-continuous counting function based on the arrival times of all order book events, t_i^0. z_i is a vector of market characteristics observed at t_i^0 and γ^k the corresponding coefficient vector, whereas $\lambda_0^k(t)=\exp(\omega^k)(x^k(t)^{p^k-1})/(1+\kappa^k x^k(t)^{p^k})$, $x^k(t)$ denotes the time elapsed since the arrival of the last buy/sell before t and ω^k, p^k and κ^k are parameters to be estimated. $s(t)$ denotes a seasonal spline function with $s(t)=1+\sum_{j=1}^{S}v_j(t-\tau_j)\cdot\mathbb{1}_{\{t>\tau_j\}}$, where τ_j, $j=1\ldots,S$ denote S nodes during a trading day and v_j are seasonality coefficients to be estimated. By indexing the sequence of transactions by i, the (2×1) vector $\tilde{\Psi}'_i=(\tilde{\Psi}^B_i,\tilde{\Psi}^S_i)$ is specified by $\tilde{\Psi}_i=\sum_{k\in\{B,S\}}(A^k\varepsilon_{i-1}+B\tilde{\Psi}_{i-1})y^k_{i-1}$ with $A^k=\{\alpha^k_j\}$ denoting a (2×1) vector and $B=\{\beta_{ij}\}$ a (2×2) matrix of parameters, and y_i^k defining an indicator variable that takes the value 1 if the i-th transaction is of type k. The innovation ε_i is given by $\varepsilon_i=\sum_{k\in\{B,S\}}(1-\Lambda^k(t^k_{N^k(t_i)-1},t^k_{N^k(t_i)}))y_i^k$, where $\Lambda^k(t^k_{i-1},t^k_i):=\int_{t^k_{i-1}}^{t^k_i}\lambda^k(s;\mathscr{F}_s)\,ds$. The sample contains all market orders of the NAB, BHP, MIM, TLS and WOW stock during the period July 8th to August 30th 2002. Standard errors are computed based on the outer product of gradients. The time scale is standardized by the average duration between two trades. The time series are re-initialized at each trading day.

Ask side						Bid side					
	NAB	BHP	MIM	TLS	WOW		NAB	BHP	MIM	TLS	WOW
ACI parameters											
ω^B	-1.14^{***}	-0.45^{***}	-0.50^{**}	-0.33	-0.31^{**}	ω^S	-0.64^{***}	-0.40^{***}	-0.57^{**}	-0.51^{***}	-0.73^{***}
p^B_B	0.86^{***}	0.89^{***}	0.86^{***}	0.87^{***}	0.84^{***}	p^S_S	0.87^{***}	0.85^{***}	0.85^{***}	0.88^{***}	0.82^{***}
κ^B_B	0.11^{***}	-3.15^{***}	0.04^{***}	0.00	-3.77^{***}	κ^S_S	0.11^{***}	-3.36^{***}	0.01	0.00	-3.44^{***}
α^B_B	0.12^{***}	0.04^{***}	0.13^{***}	0.10^{***}	0.05^{***}	α^B_S	0.05^{***}	0.00	0.00	-0.02^{***}	0.03^{***}
α^S_B	0.04^{***}	0.00	0.00	-0.02^{***}	0.03^{***}	α^S_S	0.09^{***}	0.07^{***}	0.15^{***}	0.05^{***}	0.10^{***}
β_{BB}	0.86^{***}	0.99^{***}	0.96^{***}	0.93^{***}	1.00^{***}	β_{SB}	0.01	0.01^{***}	-0.01	0.04^{***}	0.00
β_{BS}	-0.05^{***}	0.02^{***}	0.00	0.02^{***}	0.03^{***}	β_{SS}	0.97^{***}	0.97^{***}	0.93^{***}	0.98^{***}	0.94^{***}
Impact of overnight price changes											
$OCP1$	-0.56	0.11	-0.57	0.78	0.63	$OCP1$	0.69	-0.02	0.14	0.56	-1.91
$OCP2$	-0.48	0.29	0.18	1.00	0.95	$OCP2$	0.67	0.00	0.52	0.59	-1.70

Impact of the most recent transaction											
DQP	−0.06	0.00	−0.02	0.01	0.09*	*DQP*	0.17*	0.07**	0.03	0.00	−0.03
DP	−9.60***	−6.18***	−0.83***	−3.34***	−6.00***	*DP*	8.70***	7.92***	1.03***	3.39***	7.62***
*DP*1	2.37***	1.42***	−1.27	−0.24	2.47***	*DP*1	−1.42**	−0.07	0.96	0.27	−3.74***
TRV	0.17***	0.07***	0.09***	0.02	0.12***	*TRV*	−0.18***	−0.20***	−0.04	−0.04*	−0.29***
*TRV*1	0.07***	0.15***	0.09**	0.15***	0.10***	*TRV*1	−0.04	−0.12***	−0.16***	−0.17***	−0.02
DV	−0.34***	0.53***	0.71	0.75***	−0.13	*DV*	0.43***	−0.30***	−1.27***	0.24	−0.02
Impact of current limit order arrivals											
LO_{-1}	0.26***	0.12***	0.14***	0.07***	0.14***	LO_{-1}	−0.30***	−0.17***	0.04	−0.10***	−0.20***
LO_0	0.03	0.03*	−0.04	−0.01	0.01	LO_0	−0.01	−0.02	0.06*	0.03*	−0.01
LO_{+1}	0.06**	0.05***	0.06*	0.05**	−0.03	LO_{+1}	−0.02	−0.05**	−0.01	0.00	−0.07**
*CAN*0	−0.09*	0.09**	−0.14***	0.13***	0.05	*CAN*0	0.06	−0.07	−0.01	−0.20***	−0.05
*CAN*1	0.06	0.02	−0.02	−0.02	0.06	*CAN*1	−0.02	0.04	−0.06	−0.06	0.09*
Impact of the current state of the market											
AV	1.17	−0.81	0.46	0.32	0.43	*AV*	0.25	0.29	0.21	0.41	1.44
BV	0.28	0.44	−0.07	−0.32	−0.99	*BV*	−0.04	−0.90	0.30	−0.39	0.24
*BSL*02	−3.43***	−4.00***	−1.18***	−4.84***	−1.69***	*BSL*02	1.32***	4.27***	2.75***	7.45***	1.11***
*ASL*02	2.04***	3.42***	1.89***	7.46***	1.36***	*ASL*02	−1.18***	−3.39***	−0.56*	−3.05***	−0.65***
*BSL*05	−0.57	−0.71***	−1.59***	−3.36***	−1.24***	*BSL*05	1.71***	1.08***	3.00***	4.84***	0.52*
*ASL*05	1.49***	0.69**	1.51***	5.41***	0.81***	*ASL*05	−0.77**	−0.06	−0.43	−2.32***	−0.25
*BSL*10	0.34	−0.20	−2.06***	−1.42***	−0.55**	*BSL*10	0.40*	−0.12	2.29***	2.56***	0.29
*ASL*10	0.10	−0.11	1.24***	3.64***	0.02	*ASL*10	0.31	0.49**	−0.52**	−0.88**	−0.13
*BSL*20	0.27	−0.09	−2.06***	1.50**	0.22	*BSL*20	0.24	0.87***	0.97**	1.00*	0.63**
*ASL*20	0.46*	−0.12	−0.23	0.65	0.45	*ASL*20	0.31	0.00	−0.30	0.13	0.21
*BSL*50	0.28	−0.55	−2.03***	−0.49	0.69	*BSL*50	0.73***	0.81**	1.54**	0.59	0.06
*ASL*50	−0.16	−0.15	−0.02	−0.01	2.59***	*ASL*50	0.60	−0.15	0.60**	−0.54	0.70
*BSL*90	0.20	−0.33	−0.89	−0.46	0.85	*BSL*90	−0.17	0.72	0.11	−0.23	0.15
*ASL*90	1.89***	−0.02	0.72	0.39	1.14	*ASL*90	0.97	−0.11	−0.60	0.62	−2.08*
SPR	−10.32***	−6.50***	−0.46	−3.01***	−4.66***	*SPR*	−8.91***	−5.38***	−2.03**	−2.67***	−4.24***
Impact of the market activity during last 30 min											
VOLA	0.29	0.15	0.09	0.42	0.22	*VOLA*	0.24	0.04	−0.09	0.08	0.22
DMQ	−2.25	−2.26	−3.17*	−1.31	−3.74	*DMQ*	0.14	1.75	−0.98	1.81	−3.71

Table 5 (*continued*)

Ask side						Bid side					
	NAB	BHP	MIM	TLS	WOW		NAB	BHP	MIM	TLS	WOW
DASL	-0.76^{**}	0.21	-0.25	0.23	-0.22	*DASL*	-0.22	-0.44	-0.93	0.60	-0.17
DBSL	0.56	0.11	-0.54	0.25	0.79^{**}	*DBSL*	-0.43	-0.07	-0.84	-0.87^{**}	0.52
OFL	-0.12	0.02	-0.16	-0.21	-0.22	*OFL*	-0.14	0.15	0.62	0.05	0.08
OFLV	0.08^{***}	0.04^{***}	0.00	0.04^{***}	0.06^{***}	*OFLV*	0.07^{***}	0.07^{***}	0.02	0.02^{**}	0.07^{***}
Seasonality parameters											
v_1	-1.37^{***}	-0.60^{***}	-1.10^{***}	-0.88^{***}	-1.30^{***}	v_4	1.53^{***}	1.74^{***}	1.33^{***}	1.43^{***}	1.33^{***}
v_2	1.37^{***}	0.28	0.86^{**}	0.86^{***}	1.17^{***}	v_5	-0.43^{***}	0.03	-0.38	-0.05	-0.10
v_3	-0.80^{***}	-0.65^{***}	-0.32	-0.83^{***}	-0.51^{***}	v_6	0.17	0.69^{***}	1.95^{***}	0.63^{***}	0.90^{***}
Diagnostics											
n	34,296	44,604	7,395	30,878	19,787						
n^0	84,164	107,568	24,075	73,682	48,047						
LL	$-50,243$	$-67,475$	$-10,052$	$-48,269$	$-26,331$						
BIC	$-50,713$	$-67,957$	$-10,453$	$-48,724$	$-26,776$						
Residuals ask side							Residuals sell side				
Mean of $\hat{\Lambda}_i$	1.00	0.99	1.00	1.00	1.00		1.00	1.00	1.00	1.00	1.00
S.D. of $\hat{\Lambda}_i$	1.03	1.01	1.02	1.04	1.02		1.03	1.04	1.05	1.04	1.04
LB(20) of $\hat{\Lambda}_i$	57.15^{***}	78.64^{***}	15.36	27.14	49.97^{***}		27.50	34.52^{**}	12.12	63.82^{***}	30.78^{*}
Exc. disp.	3.25^{***}	0.86	0.86	3.71^{***}	1.67^{*}		2.70^{***}	3.58	2.12	3.13^{***}	2.89^{*}

Diagnostics: Log likelihood (LL), Bayes information criterion (BIC) and diagnostics (mean, standard deviation, Ljung–Box statistic and excess dispersion test) of the ACI residuals $\hat{\Lambda}_i^k$, $k \in \{B, S\}$.

best ask (bid) quote as a result of a transaction. Obviously, investors become reluctant to post a buy (sell) market order when they face worse terms of trade due to a shift of the best ask and bid quote. However, as indicated by the opposite sign of the coefficients associated with $DP1$, this effect is weakened whenever bid and ask quotes are shifted by more than one tick. Nevertheless, since the former effect is dominant, the resulting reaction of the net buy pressure is decreasing and concave which is in contrast to Hypothesis H1(b). Hence, a reduction of the terms of trade seems ultimately to reduce traders' willingness to trade on the same side of the market. This result clearly illustrates that the response of the net buy pressure on changes of the best ask or bid quotes is driven by liquidity aspects rather than by the disclosure of investors' marginal valuation.

Significantly positive (negative) effects on the buy (sell) intensity are observed from the signed transaction volume of the most recent transaction (TRV and $TRV1$). Thus, the trading intensity on the buy (sell) side is increasing with the volume of a buy (sell) order and is decreasing with the volume of a sell (buy) order. In this respect we can confirm Hypothesis H2. Nevertheless, we do not find evidence for a concave or even non-monotonous relation between the traded quantity and the resulting net buy pressure. Actually, the significantly positive coefficient of $TRV1$ indicates that the informational value of transaction volumes seems to be even increasing with the order size. Hence, we clearly reject the notion that traders tend to camouflage informational advantage.

Note that these effects hold as long as a market order does not absorb one or several levels of the opposite queue, i.e., as long as the variable DV is zero. In the case of an aggressive market order which completely removes a part of the queue, we find slight evidence for a weakening of the above effects as indicated by a negative influence on the net buy pressure.[25] In the extreme case, when the quoted volume of a market order substantially exceeds the traded volume, the resulting net effect of an aggressive buy (sell) market order on the buy intensity can even be negative (positive). This finding reveals evidence for liquidity-motivated trading behavior in the sense that traders' incentive to buy or sell decreases when the liquidity supply on the opposite side of the market declines.

6.2.2. The impact of limit order arrivals

As indicated by the coefficients associated with the variables LO_{-1}, LO_0 and LO_{+1}, we find significantly positive effects on the buy (sell) intensity after an ask (bid) order has been set below (above) the most current best ask (bid) quote. Hence, investors' incentive to buy (sell) is particularly high after the arrival of a limit order which undercuts (overbids) the most current ask (bid) price and thus improves traders' terms of trade. In line with the results above, this reflects tendencies for liquidity-motivated trading when the offered liquidity on the opposite side of the market increases, but does not support Hypothesis H3 (a). Actually, we find evidence that traders tend to take liquidity when the liquidity supply is high whereas they refrain from trading when the offered liquidity on the first levels of the queues vanishes and best ask or bid quotes shift. Nevertheless, slight evidence for similar though clearly weaker reactions of the net buy pressure are found after ask (bid) orders have been set above (below) the most current best ask (bid) quote. Interestingly, no significant effects of limit orders set at the prevailing bid/ask prices are found. Obviously investors pay particular attention to incoming limit orders which are set either above or

[25]However, this finding is not robust across the individual stocks. A possible reason might be multicollinearity effects between the variables $TRV1$ and DV.

Table 6
Marginal impacts of covariates on the net buy pressure

This table gives the estimates of the difference $\gamma^B - \gamma^S$ based on the estimates reported in Table 4 and 5. The corresponding standard errors are computed by applying the Delta method using the estimated covariance matrix of parameter estimates.

	Based on estimates in Table 4					Based on estimates in Table 5				
	NAB	BHP	MIM	TLS	WOW	NAB	BHP	MIM	TLS	WOW
Impact of overnight price changes										
*OCP*1	−3.41**	0.05	−0.23	0.62	6.84***	−1.25	0.13	−0.70	0.22	2.54
*OCP*2	−3.31**	0.18	0.15	0.90	7.04***	−1.15	0.29	−0.34	0.41	2.64
Impact of the most recent transaction										
DQP	−0.21	−0.05	−0.06**	0.01	0.12	−0.23*	−0.07*	−0.05*	0.00	0.12
DP	−30.28***	−14.39***	−1.72***	−6.32***	−13.57***	−18.30***	−14.10***	−1.86***	−6.74***	−13.62***
*DP*1	15.48***	3.30***	0.87	1.58	6.51***	3.79***	1.49**	−2.23	−0.51	6.21***
TRV	0.25***	0.20***	0.17***	−0.01	0.35***	0.35***	0.26***	0.14***	0.06**	0.41***
*TRV*1	0.14***	0.25***	0.22***	0.32***	0.08**	0.10***	0.27***	0.25***	0.33***	0.12***
DV	−0.51***	0.63***	1.29*	0.73***	−0.22	−0.77***	0.83***	1.98***	0.51*	−0.11
Impact of the current state of the market										
AV	1.00	−1.43	0.22	−1.05	−3.41	0.92	−1.10	0.26	−0.09	−1.01
BV	1.36	1.72	0.36	0.99	−0.91	0.32	1.34	−0.38	0.07	−1.23
*BSL*02	−4.09***	−6.87***	−3.65***	−11.47***	−1.90***	−4.76***	−8.27***	−3.93***	−12.29***	−2.80***
*ASL*02	2.26***	5.62***	1.88***	9.96***	1.38***	3.21***	6.81***	2.46***	10.51***	2.01***
*BSL*05	−2.26***	−1.34***	−4.89***	−7.36***	−1.34***	−2.28***	−1.79***	−4.59***	−8.20***	−1.76***
*ASL*05	1.14***	0.66	1.12*	7.64***	0.59*	2.26***	0.75	1.94***	7.74***	1.06***
*BSL*10	−0.27	−0.01	−4.06***	−3.43***	−0.78**	−0.06	−0.08	−4.36***	−3.98***	−0.84***
*ASL*10	−0.30	−0.32	1.52***	3.81***	−0.05	−0.21	−0.60**	1.75***	4.52***	0.15
*BSL*20	−0.01	−1.01***	−3.06***	1.01	0.03	0.03	−0.95***	−3.04***	0.50	−0.41
*ASL*20	0.42	0.01	0.04	−0.04	0.02	0.15	−0.12	0.07	0.52	0.24
*BSL*50	−0.61*	−1.38***	−3.45***	−1.24***	0.42	−0.45	−1.35***	−3.57***	−1.08**	0.63
*ASL*50	−0.89	0.11	−0.41	0.73*	1.43**	−0.76	0.00	−0.62	0.52	1.89**

*BSL*90	0.34	-1.42^{**}	−1.20	−1.09	0.29	0.37	−1.05	−1.00	−0.23	0.70
*ASL*90	0.26	0.12	1.56^{**}	−0.40	3.09^{**}	0.91	0.10	1.32^{*}	−0.23	3.22^{**}
SPR	-1.13^{***}	-1.72^{***}	-0.76^{**}	−0.59	−0.17	-1.41^{***}	-1.11^{**}	1.57^{*}	−0.34	−0.42
Impact of the market activity during last 30 min										
VOLA	0.13	0.11	0.10	0.23	−0.49	0.05	0.11	0.18	0.33	0.00
DMQ	-3.79^{**}	-3.42^{***}	-4.04^{*}	-4.97^{***}	−4.36	−2.40	-4.01^{***}	−2.20	−3.12	−0.03
DASL	0.02	0.06	1.49^{*}	−0.59	0.26	−0.55	0.65	0.69	−0.37	−0.05
DBSL	2.13^{***}	0.32	1.66^{*}	0.69	0.01	0.99	0.18	0.30	1.12^{**}	0.27
OFL	0.05	−0.05	−0.65	−0.18	−0.24	0.02	−0.13	−0.78	−0.26	−0.30
OFLV	0.02	-0.04^{**}	−0.03	−0.02	−0.02	0.00	−0.03	−0.02	0.01	−0.01
Impact of current limit order arrivals										
LO_{-1}						0.56^{***}	0.29^{***}	0.09^{*}	0.17^{***}	0.34^{***}
LO_{0}						0.04	0.04^{*}	-0.09^{**}	−0.03	0.02
LO_{+1}						0.08^{**}	0.10^{***}	0.07	0.05^{*}	0.04
*CAN*0						-0.15^{**}	0.16^{***}	−0.13	0.33^{***}	0.11
*CAN*1						0.08	−0.02	0.04	0.04	−0.04

below the most current best ask/bid quotes but do not increase the thickness of the book at the best quotes. Finally, we do not find a consistent impact of the arrival of a cancellation on the buy and sell intensity or on the resulting net buy pressure. Obviously, cancellations do not provide clear-cut informational value which is in contrast to Hypothesis H3 (b). Summarizing, we can conclude that in contrast to the findings in the previous subsection, the limit order arrival process has only limited explanatory power for the net buy pressure. Nevertheless, the highly significant impact of aggressive limit orders indicates that periods of increased liquidity tend to be exploited very quickly.

6.2.3. The impact of the current state of the market

We find clear evidence for a significant impact of the market depth on the ask and the bid side on both the buy and sell intensity. As revealed by the estimated coefficients of ASL and BSL, an increase of the price impact on the ask (bid) side increases (decreases) the buy intensity and decreases (increases) the sell intensity. Furthermore, the net buy pressure significantly increases (decreases) when the price dispersion of the ask (bid) queue rises and thus the steepness of the slope of the ask (bid) reaction curve declines. These findings clearly support Hypothesis H4 and confirm both the notion that standing limit prices provide information regarding traders' upper tail expectations and the idea of crowding out effects according to Parlour (1998). Furthermore, while it is shown that the order book provides valuable information beyond the best quotes, it is evident that these effects are highly significant and robust only up to a level of around 10 percent of the standing volume. For higher levels of the queue, the informational value of the order book seems to decline, which confirms the findings of Pascual and Veredas (2004). Note that the piecewise slopes of the ask and bid curves reflect the steepness of the ask and bid reaction curve; however, they do not indicate how much volume is queued in total. However, as revealed by the coefficients associated with $AVOL$ and $BVOL$, we do not find a significant relation between the total standing ask volume and the buy or sell intensity as postulated by Hypothesis H4(b). Obviously, investors pay particular attention to the relative distribution of the volume on the ask/bid sides but less to the total amount of pending quantities.

As predicted by Hypothesis H5, a large inside spread (SPR) 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. Interestingly, we find significant evidence for a negative relation between the bid-ask spread and the resulting buy–sell pressure. Hence, in periods of a tight market, investors are more willing to sell than to buy which is difficult to explain in light of market microstructure theory and requires further investigation.

6.2.4. The impact of past trading activities

No convincing evidence for a consistent impact of past market activities is found. Overnight returns reveal no clear effect on the net buy pressure. Over the cross-section of stocks we find conflicting impacts on the ask and bid intensity which do not result in a distinct effect on the net buy pressure. Slight tendencies for a decreasing buy intensity after positive returns computed over the last 30 minutes are observed. Furthermore, with few exceptions we do not find significant influences on the sell intensity and the resulting net buy pressure. However, in most cases a negative impact of the net order flow on the net buy pressure is observed which is in line with Hypothesis H7. In contrast, recent changes in the ask and bid slopes as reflected by the variables $DASL$ and $DBSL$ do not have a significant impact on the net buy pressure. These results indicate that recent trading activities are obviously sufficiently reflected by the current state of the book to which investors particularly pay attention.

Finally, in most cases we find significantly higher trading activity on both sides of the market in periods of a high order flow volatility. This confirms the notion that differences in traders' expectations increase the intensity in market order trading and is in line with Hypothesis H8. As expected, no significant impact on the resulting net buy pressure is revealed. Obviously, transitory volatility is captured more by order flow volatility than by the midquote volatility as the latter is shown to be insignificant. However, this effect might be also caused by a substantial correlation between both variables.

6.2.5. *State-dependent influences*

In order to check the robustness of the results, we extend the specifications by allowing for state-dependent impacts of individual covariates on the net buy pressure. In particular, we distinguish between a high- and low-volatility state as well as between three states associated with a highly positive, highly negative and "normal" net order flow. Four major variables are interacted with the different state combinations: recent changes in best ask/bid quotes, the signed transaction volume, the pending cumulated net ask volume and the ask and bid slope associated with the 5% volume quantile. Overall, we do not find any convincing evidence for state-dependent marginal impacts of the covariates. Rather, it turns out that the marginal effects discussed above are quite robust regarding different states in terms of volatility and signed order flow. In order to restrict the length of the paper, we do not show the regression results here.

7. Conclusions

In this paper, we study the relationship between the state of the limit order book and traders' preference for immediacy on the ask and bid side of the market. This analysis leads to a characterization of the determinants of the net buy pressure in the market. Using data from the five most liquid stocks traded at the Australian Stock Exchange (ASX) during the months of July and August 2002, we exploit detailed limit order information in order to reconstruct the complete order book. This allows the analysis of whether recent order arrivals as well as the current state of the order book have a significant influence on the trading behavior of market participants and thus on the resulting buy and sell intensity.

The contemporaneous buy and sell intensity is modelled using a bivariate version of the autoregressive conditional intensity (ACI) model proposed by Russell (1999) which we extend to allow for time-varying covariates. This approach enables us to account for the asynchronous arrival of buy and sell transactions and provides a sensible framework to account for continuous changes of the limit order book due to the arrival of limit orders as well as cancellations or amendments between individual transactions. It is shown that the consideration of *any* changes of the limit order book between two consecutive transactions significantly improves the model's goodness-of-fit compared to an intensity specification which is only updated whenever a new trade arrives. This indicates that a continuous recording of the order flow is important for the modelling of the net buy pressure.

Our empirical results are relatively stable over the cross-section of stocks and are broadly consistent with predictions from theoretical market microstructure literature. We find strong evidence for a significant impact of recent trades on the buy and sell intensity.

Actually, traders' preference for trading on a particular side of the market increases when large market orders enter the market on that side. This result confirms predictions from market microstructure theory that order volumes reflect traders' marginal valuations and have information value. We even observe that the marginal impact of order volumes tends to be increasing with the traded quantity. Hence, no evidence is found that informed investors tend to hide informational advantage by trading medium quantities instead of large quantities (e.g., Barclay and Warner, 1993). Overall, we find that recent market order arrivals have a clearly stronger effect on the buy and sell intensity than limit order arrivals or cancellations. Particularly for the latter we do not find distinct influences.

Furthermore, we show that traders' decision of when and where to submit a market order is affected by the current state of the order book, which confirms the results of Ranaldo (2004) and Pascual and Veredas (2004). Our findings support the hypothesis that traders infer from the standing limit prices with respect to expected price movements. In fact, the net buy pressure increases (decreases) when the order queues on the ask (bid) side reveal a lower depth and thus a higher dispersion of posted limit prices. This result is consistent with the predictions by Glosten's (1994) model where pending limit prices reflect investors' underlying upper or lower tail expectations and thus have informational value. It is also consistent with Foucault's (1999) mechanism of crowding out where an increase (decrease) in the depth leads to a decrease (increase) of the execution probability of limit orders. Our findings indicate that the information value of the book clearly declines in the higher levels of the queues, with the influence of the ask and bid slopes found to be significant only up to the 10 percent volume quantile.

Interestingly, limited evidence for the impact of recent market activities during the last 30 min is found. Obviously, the current state of the market is sufficiently characterized by the book and investors pay particular attention to the later instead of observing the trading history. Nevertheless, the recent net order flow as well as the recent order flow volatility turn out to significantly influence the current buy and sell intensity. In contrast to the predictions of the Foucault (1999) model we find an increased trading intensity on both sides of the market when the order flow volatility and thus the uncertainty in the market during the last 30 min has been high.

In addition to the conclusion that traders infer from the information provided by the book we also find relationships that we attribute to "liquidity effects." Actually, traders' preference for immediacy declines after the arrival of a market order which completely absorbs the first level(s) of the order queue and implies an upward (downward) shift of the best ask (bid) price. On the other hand, the buy (sell) intensity increases after the arrival of an ask (bid) limit order placed below (above) the current best ask (bid) quote which indicates that investors tend to take liquidity when the liquidity supply on the opposite side of the market is high.

Empirical evidence for significant interdependences between both sides of the market confirm the findings of Ranaldo (2004). The trading intensity on one 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 pressure is particularly strong when the market reveals imbalances between the bid and ask sides. These findings confirm the results of Chordia et al. (2002) who illustrate, based on daily data, that daily order imbalances are a major source of trading activity and important determinants of market returns. We have demonstrated that such effects cannot only be identified on an aggregated level but also on the transaction level.

Overall, this study provides insights into the questions of how traders learn from order book information and how the latter influences the trading intensity on both sides of the market as well as the resulting net buy pressure. The fact that traders' preference for immediacy on the buy and sell side is significantly influenced by the state of the book 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.

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