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The interaction between order imbalance and stock price

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Abstract

We study the interaction between imbalance of bid and ask orders and stock return, using two metrics for order imbalance and two whole years of data on every order placed for the 20 stocks most actively traded on the Australian market in those two years. We find bi-directional causality between imbalance and return, but not beyond a single day. We also see that the number of orders can explain current return, but the dollar value of orders can explain both current and future return. The speed of adjustment of price to order imbalance in Australia may be slow (up to a day), but it is no slower than the NYSE. Price stabilisation behaviour is not present in Australia, suggesting that the order imbalance/return relationship is most likely informational. © 1997 Elsevier Science B.V.

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1. Introduction

There is evidence that order flow and the existing limit order book interact with stock return in the short run. In particular, a temporal imbalance between buy and sell orders arriving at a market increases the likelihood that informed traders are attempting to pre-empt good or bad news, and prices and further orders react accordingly. Market structure may play an important role here. In one type of

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market, regulatory constraints force market makers to act to smooth out the impact of order imbalance, allowing a gentle rather than ''jerky'' transition from one equilibrium state to another. This price stabilisation process will hence slow the reaction of price to order imbalance. In a second type of market, these regulatory constraints are not in place, so we might expect the price reaction to occur earlier and subsequent reverberations to be less significant.

An excellent example of the first type is the New York Stock Exchange (NYSE), which has a limit order book that is private apart from the quotes posted by specialists. They are charged with the task of ''leaning against the wind'' (Madhavan and Smidt, 1991, p. 118) to stabilise prices in the event of an order imbalance. By contrast, the Australian Stock Exchange (ASX) is an electronic order-driven market, with a public limit order book affording a high level of market transparency. There is no formal NYSE-style price stabilisation mechanism at work, although trading is stopped when a company makes an announcement that the ASX deems to be price-sensitive, typically for about 10 minutes while brokers update existing orders or enter new ones. It is hence an excellent example of the second type of market.

So, a study of order imbalance in Australia will allow conclusions to be drawn which will contrast with results from the NYSE. This is the main focus of our paper.

2. Prior research on order imbalance and stock returns on the NYSE and ASX

2.1. NYSE

On the NYSE a monopolistic market maker – called a specialist – quotes prices and volumes at which he is willing to trade to any trader who asks for a quote. The specialist sets the bid–ask spread to compensate himself for inventory costs, processing and administration costs, and for any adverse selection costs he perceives he faces from the order flow. He also adds a monopolistic rent to the spread, since he does not face direct competition. While to outsiders this may seem a little inefficient (why not introduce competition?) strong arguments exist to maintain the system as it stands. Among them is the idea from Glosten (1989) that a monopolist can spread his profits over multiple trades, so he sometimes can keep a market open when a market with competing market makers would close. Another is that since the specialist is charged by the NYSE to stabilise prices, in return for the monopolistic position, volatility may be lower and price fluctuations may be offset. But by absorbing the imbalance into his inventory, he may spread out the price reaction that surely must follow the initial order imbalance.

Much of the work on the NYSE has assessed the impact of order imbalance indirectly; only a few have assessed its impact directly. The earliest work is Marsh and Rock (1986, p. 22) who find significant negative autocorrelation in hourly order imbalance out to five lags. This suggests that buys and sells arrive somewhat separately, and in ''bunches''. Hasbrouck and Ho (1987), Hasbrouck (1991) and Walsh (1997) partly confirm this by finding that buys tend to follow buys and sells to follow sells. It is still an open question whether this pattern incorporates an informational effect or is driven wholly by the underlying order arrival process itself. We address the question by seeing if prices react significantly more quickly in a market without these stabilisers: that is, in Australia.

Marsh and Rock (1986) examine the relationship between order imbalance (measured as standardised cumulative net trading volume – (asks − bids)/(asks + bids)) and return (measured as the percentage change in the bid–ask midpoint). The analysis is performed using every tick (whenever the bid or ask quote changed) and with hourly sampling. They presume that causality flows from volume to price change, and use price change as the dependent variable in the regression. Their data are three random samples of 50 companies, one from each of the NYSE, AMEX and NASDAQ markets, for the months of March and April 1985. The data used are time-stamped best bid and ask, and the trading volume and prices. Trades inside the spread are ignored. Marsh and Rock (1986) show that there is a significant relationship between order imbalance and return. Order imbalance exhibits a strong positive relationship with contemporaneous return, using both hourly sampling and tick-by-tick data. They find a strong size effect; in both sets of regressions, the impact of a given order imbalance (e.g., 10,000 shares or 1000 sell orders) is less for larger firms. At the same time, the explanatory power of the relationship improves with firm size, from an average R^2 value of 9% for the smallest quintile up to 25% for the largest quintile.

Blume et al. (1989) examine the order imbalance around October 19 and 20, 1987. They use 15-minute returns and an estimate of contemporaneous aggregate order imbalance based on the sum of the order imbalances of all stocks appearing at the bid and ask prices. (It is an estimate because it ignores trades inside the spread.) They find a strong relationship between imbalance and return, but the relationship is much stronger for firms in the S&P500 than for other firms. They suggest these results are ''consistent with, but do not prove'' (p. 843) the hypothesis that the S&P500 firms experienced a much greater decline in price (and subsequent rebound) on these two days because of the excess selling pressure. Madhavan and Smidt (1993) find that specialists revise their inventory levels slowly, with less than half the revision taking place in a week, even after correcting for changes in the desired inventory level. Further, they find that daily price change is strongly related to the information contained in the (non-block) order imbalance over the day; that is, the unexpected component of the order imbalance. (Block order imbalance contains little up-to-date information, suggesting that any information has already leaked in the ''upstairs'' market.) Huang and Stoll (1994) use one-day lagged imbalance in volume quoted by the specialist to detect any impact it might have on daily return (again using bid–ask midpoint).

Among other results, they find a strong relationship between this quoted order imbalance and the return: the more the number of net shares being sold, the greater the price decrease.

Lee (1992) examines the imbalance of trade direction (the net number of sell orders, not the net number of shares sold) and finds that the order imbalance before an earnings announcement is indistinguishable from any other time. After the announcement, there is no difference between the number of large buys and sells, but there is a significantly greater number of buys than sells for small orders. This is independent of whether the announcement contains good or bad news, or what the firm size is, or even how much total volume is traded. Rather than suggest that returns are driven by order imbalance, Lee's (1992) results suggest the opposite.

We conclude that order imbalance (however measured) appears to have a significant effect on returns, both contemporaneously and lagged, and is autocorrelated, even at fine sampling intervals. To say that order imbalance causes some part of the returns is too strong, based on current evidence. We investigate this here, along with bi-directional causality. Also, the rate of correction of order imbalance has never been studied; it is a feature of this paper.

2.2. ASX

We know of two Australian studies of order imbalance. Yuen (1993) performs a study similar to Lee (1992) by examining the differences in trading volume of large and small orders around earnings and dividends announcements. In contrast to Lee (1992), she finds a significantly lower volume of small buys both before and after the announcements compared to other periods, suggesting that the net volume of buy orders has no predictive power; it is not informational.

Kua (1993) uses a large ASX database to investigate the probability of a trade occurring at the ask price, conditioned on limit order imbalance immediately prior to the placement of the market order that triggered the trade. She finds that imbalance in live limit orders has no predictive power when measured using dollar volume, but curiously, that the probability of a trade at the ask decreases with a greater net number of buy orders. If correct, this could mean continuations are more common than reversals, which is contrary to much previous evidence, for example, Niederhoffer and Osborne (1966). On the other hand, it does suggest that buys tend to follow buys and sells to follow sells, which has been documented elsewhere (see above).

3. Research questions

We have seen that order imbalance and returns appear to be related. If the market uses either on-going price stabilisation or circuit breakers and trading halts, it can cope with an order imbalance crisis (like October 1987). However, the market's reaction to non-crisis levels is unclear. Is the price reaction to order imbalance informational, or is it simply a smaller scale of the crisis reaction? Further, the exact causal nature of this relationship, if there is one, is unknown; for instance, does order imbalance lead price change, or vice versa?

In summary, we examine the following questions.

1. Does order imbalance correlate with return?
2. Which causes which?
3. Is the effect informational or simply a result of price-smoothing?

On this third question, rather than examine the impact of using a trading halt, we examine the absence of trading halts. By comparing results in Australia, where no price-smoothing intervention is required, to the NYSE, where price smoothing supposedly is at work all the time, we may be able to gauge whether there is a difference. If we do see a difference, we might conclude that the impact is due to price smoothing on the NYSE. The direction of this difference is unclear, because while it would slow down the price impact of an order imbalance in transaction time (i.e., it might take more orders for the impact to be incorporated), in calendar time the result may in fact be faster, because of the considerably greater volume on the NYSE. If we see no difference, we can either conclude that (a) the price smoothing impact exactly outweighs the increased volume impact (which seems unlikely), or (b) price smoothing is not driving this reaction at all: the price change/order imbalance relationship is an informational one.

4. Methodology

4.1. Trading on the ASX

The Australian market differs in important ways from the NYSE. The NYSE may be characterised as an order-driven market that opens with a call and requires its dealers (specialists), who maintain private limit order books, to provide liquidity throughout the day. The ASX is also an order-driven market. But in contrast with the NYSE, the ASX order book is highly transparent, trading is wholly electronic and there are no appointed dealers or specialists, although some brokers act as pseudo-specialists by regularly providing trade facilitation services. A form of double auction applies until the ASX opens, when the market is immediately cleared. Thereafter, a trade occurs only when an incoming market order ''hits'' the best (highest priority) opposing limit order.

The ASX's trading system, SEATS, functions through a series of interconnected terminals located principally in brokers' offices. They and members of the public can observe in real time almost the entire limit order book for each listed security. The SEATS screen displays, for a given share, each unfilled limit order's broker identification number, quantity and price, although for orders above a minimum size the quantity may be hidden.

Two major rules determine an order's execution priority: price and time. [1] An imbalance of buy orders implies a longer expected wait in the buy side queue and a larger risk that a buyer's limit order will not execute. [2] New buyers have to pay a premium for liquidity because in order to gain priority they must over-bid the existing best price. The same priority rules apply when the price or volume of an order is amended. When the volume is raised, the original portion (volume) of the amended order retains its priority and the additional volume is placed at the end of the queue at that price. When the volume is lowered, the order retains its priority. When the price of an order is amended it is placed at the end of the queue at the new price.

Regular trading hours are 10 a.m. to 4 p.m. The exact market opening time is random and within ± 15 seconds of 10 a.m. Opening is staggered over the first few minutes, with trading commencing by alphabetical groups. From 7.30 a.m. until market opening and for an hour after closing, SEATS is placed into ''pre-opening mode'', when new bids and asks may be entered and existing orders amended or deleted. [3] From 5 p.m. to 7 p.m. the market is in ''adjustment mode'', when existing orders may be cancelled or amended away from the market but they can not be improved nor can new orders be entered. Overnight, the bid and ask queues are maintained, except that certain orders are purged from the market. These include (a) stale orders, [4] (b) orders that were ''good for the day only'' or otherwise have reached their expiry date, and (c) orders for shares that are to change their basis of quotation [5] overnight. At all other times SEATS is either in inquiry mode (when users can retrieve existing information but no new bids or asks may be entered or amendments made) or in suspend mode (no entries or inquiries can be made).

4.2. Data and method

The database includes a complete record of every new order placed, amendments to and cancellations of orders, and the trades that occurred on SEATS from January 1994 to December 1995. Our sample consists of the 20 stocks that were

[1] The system assigns unique transaction numbers and processes transactions sequentially. Hence two orders never have the same priority.

[2] Note that these trading rules differ from those on the NYSE, where orders large enough to satisfy the remaining order after the price parity rule is applied have priority over smaller orders, even where the smaller orders were placed first.

[3] Pre-opening procedures also apply following ''announcement halts'', which occur when a company makes a price sensitive announcement.

[4] A stale order is defined as one which was sufficiently close to the market price upon entry but is now more than the maximum allowable number of price steps away from it, due to market movements over time. Orders more than 45 price steps (ticks) away from the best price on their side of the market are ''stale'' and are purged/deleted overnight.

[5] For example, when the share is first quoted ex dividend or is split.

continuously and most actively traded on the ASX over the two year period. They traded on average from about 120 (NCM) to more than 500 times a day (BHP), together accounting for 38% of all on-market trades by number and 56% by value.

We construct two imbalance metrics, one based on the number of orders and the other on their size ($value). Imbalance is then defined as the total number (value) of ask orders divided by the sum of bids and asks. By construction, the imbalance metric is bounded by $+1$ (when there are no bids) and zero (when there are no asks); it is 0.5 if bids equal asks. The metric based on dollar value measures the information content of the size of the orders arriving as well as the frequency of their arrival. If there is extra information in size, this metric should pick it up. On the other hand, the number metric does not contain this information, and hence has the effect of weighting smaller orders more heavily than they might otherwise be. Therefore, by comparing the results from both metrics we can obtain interesting conclusions regarding the differential impacts of large and small orders. While interesting, this exploration is left to future work.

Stock return is defined as the difference between the natural logarithms of two successive prices. Log returns are used because they mitigate bias induced by the bid/ask spread and price discreteness (Mucklow, 1991). That bias can be negligible for the daily returns of higher priced stocks, but for intraday returns it is greater. Price is measured by the average of the best bid and best ask price, to reduce measurement problems associated with bid/ask bounce and non-trading. [6]

We adopt a bivariate vector auto-regression (VAR), based on a detailed specification search to ensure that the best model and metrics are used. Formally, the model is

$$R_t = \sum_{k=1}^{k=n} \alpha_k R_{t-k} + \cdots + \sum_{k=0}^{k=n} \beta_k \mathrm{OI}_{t-k} + u_t, \tag{1}$$

$$\mathrm{OI}_t = \sum_{k=0}^{k=n} \delta_k R_{t-k} + \cdots + \sum_{k=1}^{k=n} \gamma_k \mathrm{OI}_{t-k} + v_t, \tag{2}$$

where α, β, δ and γ are the parameters, u and v are the error terms and t is the time period. Eqs. (1) and (2) as stated relate return, R (order imbalance, OI) to lagged returns (order imbalance) and contemporaneous and lagged order imbalance (returns). The number of lags, denoted by n, varies according to the particular version of the model that is fitted. Also, sometimes the model is fitted without the contemporaneous value of the other variable appearing on the R.H.S. Regressions are fitted separately for each firm. A variety of diagnostics were used to increase our confidence in the correctness of the model and the inferences we draw from it.

[6] According to Blume et al. (1989), the potential bias when using last transaction prices is not substantial.

5. Results

To examine the causality between order imbalance and returns, three data sets are developed for each stock separately. The first set consists of daily data, from close on one day to close on the next; the second divides the first into two periods, from close to open and open to close; the third set further divides the trading day into the six trading hours, to yield seven periods – close to open, plus the six trading hours from about 10 a.m. to 4 p.m. The order flow measures are as previously defined and the return series are based on the bid–ask midpoint at the end of each period. Table 1 contains means of the relevant variables for each stock. Return is on average positive for 11 of the 20 stocks. (Its standard deviation, not reported in the table, does not decline directly with the root of the number of sub-periods in the day, consistent with some autocorrelation in returns and a higher variance in overnight returns.) For 16 stocks the imbalance by number was less than by value.

Table 1
Mean return (%) and imbalance in the number and value of order flow

	Day			Day/night			Hourly		
ASX code	Ret	OI#	OIV	Ret	OI#	OIV	Ret	OI#	OIV
AMC	−0.01	0.36	0.51	0.00	0.35	0.48	0.00	0.35	0.48
ANZ	0.05	0.48	0.49	0.03	0.48	0.50	0.01	0.48	0.49
BHP	0.02	0.47	0.50	0.01	0.48	0.51	0.00	0.47	0.50
BOR	−0.05	0.40	0.50	−0.02	0.41	0.49	−0.01	0.40	0.49
CBA	0.02	0.45	0.51	0.02	0.46	0.51	0.00	0.45	0.49
CML	−0.05	0.24	0.50	−0.02	0.23	0.50	−0.01	0.23	0.47
CRA	0.03	0.48	0.50	0.02	0.50	0.50	0.00	0.49	0.50
CSR	−0.02	0.43	0.50	−0.01	0.44	0.50	0.00	0.43	0.49
GIO	−0.01	0.54	0.48	0.00	0.56	0.51	0.00	0.55	0.50
MIM	−0.09	0.46	0.49	−0.03	0.46	0.49	−0.01	0.46	0.49
NAB	0.00	0.32	0.50	0.00	0.32	0.51	0.00	0.31	0.49
NBH	0.01	0.46	0.49	0.01	0.47	0.49	0.00	0.46	0.48
NCM	−0.04	0.52	0.48	−0.02	0.55	0.49	0.00	0.54	0.49
NCP	0.01	0.43	0.51	0.01	0.44	0.52	0.00	0.43	0.50
PDP	−0.11	0.43	0.49	−0.05	0.44	0.51	−0.01	0.42	0.50
SRP	−0.02	0.47	0.48	0.00	0.48	0.50	0.00	0.47	0.49
STO	0.00	0.38	0.50	0.00	0.37	0.50	0.00	0.37	0.47
WBC	0.05	0.54	0.48	0.03	0.56	0.52	0.01	0.55	0.50
WMC	0.05	0.47	0.49	0.02	0.50	0.51	0.01	0.48	0.49
WOW	0.01	0.53	0.47	0.00	0.55	0.49	0.00	0.54	0.50
Avge.	−0.01	0.44	0.49	0.00	0.45	0.50	0.00	0.44	0.49

20 ASX-listed stocks actively traded from January 1994 to December 1995.
Imbalance is the ratio of Asks to Bids + Asks. ''Day'' refers to a single daily period, close-to-close; ''Day/night''' divides each day into two periods, close-to-open and open-to-close; and ''Hourly'' divides each day into seven periods, close-to-open and the six trading hours.

Data analysis proceeded as follows. [7] Each endogenous variable (return and order imbalance) is regressed on lagged values of itself and on the contemporaneous and lagged values of the other endogenous variable. Enders (1995, p 313) notes that if a VAR specification is symmetric with identical lag lengths (which is almost true of the above specification) it is estimated via OLS. If not, a maximum likelihood approach is better. Here, we use OLS on the separate equations, even though the equations are not exactly symmetric. To examine the impact of the contemporaneous variables, the regressions are also run without them, as a sort of specification test. The equations are then truly symmetric and OLS is consistent and efficient.

An augmented Dickey–Fuller test (Harvey, 1990, pp. 81–82) was initially used to test for unit roots in the two variables. All variables were stationary at conventional levels of significance. To select lag length, a general-to-specific approach was used, and three tests of lag length were employed; autocorrelation of residuals, a likelihood ratio test of rejection of a lag, and the Schwarz criterion test (Judge et al., 1985, pp. 245–246). All were consistent in suggesting that the relationship (whatever it is) appears to last no longer than a day.

Among other diagnostics, a Chow test (Greene, 1991, p. 218) and a one-step ahead forecast error test were conducted for parameter constancy with a test sub-set of six of the 20 stocks. The parameters appeared to remain constant throughout the data set, suggesting that we can rely on both the significance and the level of the parameter estimates. Also, tests for non-linearity in the model (specifically, a RESET test and an F-test of squared residuals regressed on squares and cross-products of regressors) were conducted for the same six stocks but could not reject linearity or correct functional form of the model. Residuals were found to fail normality and heteroscedasticity tests commonly, and tests for autocorrelation less commonly. These are a feature of most high frequency data in finance. We can partly correct the problems by using White's heteroscedasticity-consistent standard errors, which allow inference without concern for heteroscedasticity. In another set of tests, we removed intraday mean effects from returns and order imbalance and found the results were largely unaffected. Given all of these diagnostics, we can be reasonably assured of the causality tests that we run.

We conducted a Granger causality test, where we simply examine, in each endogenous variable's regression, the significance of the set of coefficients of the

[7] A number of different specifications were used in exploring the causal structure. Returns using last trade values rather than bid–ask midpoints, and using daily closing prices were used. Raw order flow metrics and other measures of order imbalance were also studied. Every permutation of these specifications was examined in the same way as the analysis detailed below. The same analysis was performed on just the trading day – that is, just periods 2 to 7 – with the order flow from close to open being added into period 2. Also, the bid-to-bid and ask-to-ask returns were examined in this way. We found that the bid and ask side returns sometimes behaved differently, although the explanation for this is not clear. A brief synopsis of these results may be obtained from the authors.

''other'' endogenous variable, including its contemporaneous value. [8] The conclusions would be:

- If neither set of coefficients is significant, no causality.
- If only one is significant, uni-directional causality.
- If both are significant, bi-directional causality.

Causality test results are summarised in Table 2. The hypothesised direction of causality is indicated by the arrow in the top row of the main body of the table, for instance from return to imbalance in the value of new orders. The second row indicates the data set to which the cell entries relate: close-to-close (''Day''); close-to-open plus open-to-close (''Day/night''); and close-to-open plus the six trading hours (''Hourly''). The value in each cell is the tail probability from a likelihood ratio test for significance of the set of parameter estimates. For instance, a value of 0.05 or less suggests that we can reject the null hypothesis of no causality with 95% confidence.

Several interesting conclusions follow from these results. Granger causality from order imbalance (value) to return is bi-directional when the contemporaneous values are included and imbalance relates to the value of orders entered each hour. This result is significant at the 1% level for 19 of the 20 stocks. The results are less persuasive when imbalance is measured by number of orders each hour: we reject the null in favour of bi-directional causality in only nine stocks at the 5% level and five at 1%. With both imbalance measures, bi-directional causality is significant for progressively fewer stocks as we increase the length of the measurement period. On the other hand, there is extremely strong evidence of return ''causing'' imbalance in the number of orders each hour, and it carries over into the daily order flow as well.

We also estimated the relationships when the contemporaneous terms are omitted. [9] The significance of the causality declines as we reduce sampling frequency. However, other results change substantially. Causality from number imbalance to return is significant in only one case, but in the reverse direction it is strong, being rejected only once. If value imbalance is used, strong bi-directional causality is found. Note that contemporaneous returns and order imbalance appear to be related in an important way. Imbalance in the number of orders can explain current but not future return, whereas imbalance in their dollar value can explain both. From our discussion of the different metrics, this conclusion suggests that smaller trades (and hence perhaps smaller traders) do not react immediately to the ''news'' in returns, but tend to follow. Larger trades appear to react more quickly,

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[8] A second causality test – a modified Sims test (Gweke et al., 1983), which uses future and lagged values of the independent variable in the regression to see if they predict the present value of the dependent variable – was also conducted for the sub-set of six stocks that were chosen for more searching analysis. The results of the Granger and modified Sims tests were consistent and only the Granger test statistics are reported here.

[9] The results are not tabulated in the interests of brevity but are available from the authors.

Table 2
p-values for Granger causality tests of the interaction between return and imbalance in order flow

	Return → OI value			OI value → Return			Return → OI number			OI number → Return		
ASX code	Day	Day/night	Hourly	Day	Day/night	Hourly	Day	Day/night	Hourly	Day	Day/night	Hourly
AMC	0.18	0.49	0.00 *	0.00 *	0.01 *	0.00 *	0.00 *	0.00 *	0.00 *	0.48	0.51	0.07
ANZ	0.17	0.28	0.00 *	0.08	0.23	0.00 *	0.00 *	0.00 *	0.00 *	0.28	0.07	0.83
BHP	0.45	0.01 *	0.00 *	0.13	0.02	0.00 *	0.00 *	0.00 *	0.00 *	0.63	0.03	0.26
BOR	0.30	0.11	0.00 *	0.31	0.05	0.00 *	0.00 *	0.00 *	0.00 *	0.54	0.25	0.83
CBA	0.31	0.71	0.00 *	0.01 *	0.81	0.00 *	0.00 *	0.00 *	0.00 *	0.93	0.99	0.02
CML	0.35	0.19	0.00 *	0.00 *	0.29	0.00 *	0.00 *	0.00 *	0.00 *	0.26	0.05	0.00 *
CRA	0.02	0.32	0.00 *	0.11	0.13	0.00 *	0.01 *	0.16	0.00 *	0.05	0.82	0.00 *
CSR	0.01	0.48	0.00 *	0.08	0.40	0.00 *	0.00 *	0.00 *	0.00 *	0.07	0.00 *	0.61
GIO	0.07	0.21	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *	0.23	0.31	0.02
MIM	0.22	1.00	0.00 *	0.21	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *	0.38	0.13	0.00 *
NAB	0.22	0.00 *	0.00 *	0.07	0.01	0.00 *	0.00 *	0.00 *	0.00 *	0.28	0.03	0.00 *
NBH	0.07	0.09	0.01 *	0.01 *	0.08	0.00 *	0.00 *	0.00 *	0.00 *	0.17	0.66	0.09
NCM	0.03	0.92	0.12	0.07	0.19	0.00 *	0.00 *	0.00 *	0.00 *	0.05	0.09	0.01 *
NCP	0.00 *	0.27	0.00 *	0.02	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *	0.76	0.77	0.87
PDP	0.02	0.07	0.00 *	0.33	0.14	0.00 *	0.00 *	0.00 *	0.00 *	0.76	0.96	0.03
SRP	0.17	0.49	0.00 *	0.00 *	0.14	0.00 *	0.00 *	0.00 *	0.00 *	0.88	0.61	0.74
STO	0.00 *	0.41	0.00 *	0.00 *	0.07	0.00 *	0.00 *	0.00 *	0.00 *	0.15	0.52	0.82
WBC	0.04	0.01 *	0.00 *	0.00 *	0.04	0.00 *	0.00 *	0.00 *	0.00 *	0.02	0.04	0.07
WMC	0.03	0.08	0.01	0.03	0.00 *	0.00 *	0.00 *	0.00 *	0.00 *	0.42	0.24	0.03
WOW	0.11	0.03	0.00	0.21	0.02	0.00 *	0.00 *	0.00 *	0.00 *	0.98	0.83	0.29
Avge.	0.14	0.31	0.01	0.08	0.13	0.00	0.00	0.01	0.00	0.42	0.40	0.28
N ($p < 0.01$)	2	3	17	8	5	20	20	19	20	0	1	5

20 ASX-listed stocks actively traded from January 1994 to December 1995. Contemporaneous values are included.
Imbalance is the ratio of Asks to Bids + Asks. ''Day'' refers to a single daily period, close-to-close; ''Day/night'' divides each day into two periods, close-to-open and open-to-close; and ''Hourly'' divides each day into seven periods, close-to-open and the six trading hours. Daily and Day/night tests use two lags, hourly tests use three lags. The symbol ''A → B'' indicates that B was the dependent variable and the explanatory variables were lagged values of B and lagged and contemporaneous values of A. The *p*-value, which is shown correct to 2dp, indicates the probability that the observed causal effect, the direction being indicated by the symbol '' → '', was a chance event. That is, if $p < 0.01$, we are 99% confident that the causality was not random (indicated by a *).

indicating perhaps that they are more informed than smaller trades. This would support previous work (for example, Walsh, 1996). We cannot, however, refute the stealth trading hypothesis of Barclay and Warner (1993) here, without examining the linearity of the relationship. Again, we leave this to future work.

In summary, we can see that the strong bi-directional causality at the hourly level between returns and number imbalance is probably due to the contemporaneous relationship. When the contemporaneous terms are omitted, the causality remains bi-directional between returns and imbalance by value but becomes uni-directional from returns to number imbalance. The two order flow measures – imbalance by number and value – behave quite differently, and different tests yield the same type of difference between them. It seems that imbalance in the number of orders has substantially less impact on return than does their dollar value, whereas return appears to drive both number and value of orders.

While the causality tests in Table 2 indicate how confidently the null can be rejected, we also report the explanatory power of three specifications: where the ''other'' variable's lagged and contemporaneous values are included on the R.H.S.; where only its lagged values are included; and where it is totally excluded, so that the R.H.S. variables are exclusively lagged values of the dependent variable itself. Tables 3 and 4 relate to return and order imbalance by value and number, respectively.

Table 3 indicates negligible autocorrelation in hourly value imbalance and detectable but nevertheless weak autocorrelation in daily imbalance as well (maximum R^2 is 0.07; see columns headed ''Excl. R''). Including the lagged values of the ''other'' variable adds little explanatory power, most of which is associated with its contemporaneous value. Overall explanatory power is comparable, averaging 12–15%, for the return and order imbalance regressions and regardless of the data set (Day, Day/Night and Hourly). Comparing Tables 3 and 4 again shows the contemporaneous relationship of return to imbalance is weaker for number than value. [10] In contrast with the negligible autocorrelation in hourly value imbalance, imbalance in the number of orders is strongly autocorrelated (refer column 10 of Table 4; average R^2 is 0.26), and more strongly again for daily imbalance (column 4; average is 0.48), where the overall explanatory power of the imbalance regression is at least 80% for three companies (BOR, CBA, and PDP) and averages 56% over the 20 (column 2). In this case (i.e., where number imbalance is being predicted), although Table 2 shows return ''causes'' imbalance, including the contemporaneous return adds little to the regression's explanatory power with daily data, and about 5% on average with hourly (and day/night) data.

Finally, we present graphical representations of the response of (a) return and (b) OI value to a single innovation (or ''impulse'') in (1) return or (2) imbalance in the value of the order flow. We confine our graphs to those derived from the hourly data set. The graphs are drawn using the coefficients from the regressions of return on imbalance that are represented in columns 8 and 17 of Table 3; i.e., the contemporaneous values of the ''other'' variable are included among the regressors. To generate the graphs, Fig. 1 for instance assumes an initial return innovation (exogenous shock) sufficient to induce a return of 1% in the first hour; we assume the initial shock is to price and not to imbalance in the value of orders per se, although order imbalance is naturally affected via the price–order imbal-

[10] That is, including the contemporaneous return adds little to the explanatory power of the regression (Eq. (2)).

Table 3
R^2 values for OLS regressions between return and imbalance in the value of new orders placed

	Return → OI value									OI value → Return								
	Day			Day/Night			Hourly			Day			Day/ Night			Hourly		
ASX code	Incl. Ro	Excl. Ro	Excl. R	Incl. Ro	Excl. Ro	Excl. R	Incl. Ro	Excl. Ro	Excl. R	Incl. OIo	Excl. OIo	Excl. OI	Incl. OIo	Excl. OIo	Excl. OI	Incl. OIo	Excl. OIo	Excl. OI
AMC	0.14	0.05	0.04	0.13	0.02	0.02	0.15	0.01	0.00	0.15	0.05	0.02	0.14	0.04	0.03	0.15	0.02	0.01
ANZ	0.13	0.04	0.03	0.13	0.01	0.01	0.15	0.01	0.00	0.12	0.03	0.02	0.14	0.02	0.01	0.16	0.02	0.01
BHP	0.18	0.05	0.05	0.12	0.02	0.01	0.14	0.01	0.00	0.16	0.02	0.01	0.13	0.03	0.02	0.15	0.02	0.01
BOR	0.12	0.04	0.03	0.13	0.01	0.01	0.15	0.02	0.01	0.11	0.03	0.02	0.17	0.05	0.05	0.18	0.05	0.04
CBA	0.12	0.03	0.02	0.15	0.00	0.00	0.17	0.01	0.00	0.14	0.05	0.03	0.18	0.03	0.03	0.17	0.02	0.01
CML	0.10	0.01	0.01	0.11	0.00	0.00	0.14	0.01	0.00	0.11	0.03	0.00	0.13	0.03	0.02	0.14	0.03	0.02
CRA	0.09	0.03	0.01	0.04	0.00	0.00	0.08	0.00	0.00	0.08	0.03	0.02	0.07	0.03	0.03	0.09	0.02	0.01
CSR	0.06	0.03	0.01	0.10	0.01	0.01	0.12	0.02	0.00	0.05	0.01	0.00	0.10	0.01	0.01	0.14	0.04	0.03
GIO	0.14	0.03	0.02	0.14	0.01	0.00	0.13	0.01	0.00	0.15	0.03	0.00	0.16	0.04	0.02	0.15	0.03	0.01
MIM	0.16	0.01	0.00	0.13	0.00	0.00	0.13	0.00	0.00	0.17	0.02	0.01	0.16	0.03	0.01	0.14	0.02	0.01
NAB	0.12	0.02	0.02	0.12	0.02	0.00	0.14	0.01	0.00	0.13	0.03	0.02	0.11	0.01	0.00	0.15	0.01	0.01
NBH	0.17	0.04	0.03	0.12	0.01	0.01	0.13	0.00	0.00	0.16	0.03	0.01	0.12	0.02	0.01	0.14	0.01	0.01
NCM	0.24	0.08	0.07	0.17	0.07	0.07	0.12	0.00	0.00	0.18	0.03	0.02	0.09	0.02	0.02	0.13	0.01	0.00
NCP	0.08	0.05	0.01	0.05	0.00	0.00	0.13	0.01	0.00	0.06	0.03	0.01	0.06	0.01	0.00	0.13	0.01	0.00
PDP	0.13	0.03	0.01	0.11	0.02	0.01	0.08	0.01	0.00	0.12	0.01	0.01	0.10	0.00	0.00	0.08	0.01	0.00
SRP	0.14	0.05	0.02	0.13	0.01	0.01	0.15	0.01	0.00	0.14	0.05	0.02	0.14	0.02	0.01	0.16	0.02	0.02
STO	0.10	0.03	0.00	0.10	0.01	0.00	0.12	0.01	0.00	0.11	0.04	0.02	0.12	0.03	0.02	0.13	0.02	0.02
WBC	0.14	0.02	0.01	0.13	0.02	0.01	0.14	0.01	0.00	0.15	0.03	0.00	0.12	0.01	0.00	0.15	0.02	0.01
WMC	0.30	0.03	0.02	0.13	0.01	0.01	0.17	0.01	0.00	0.31	0.04	0.03	0.16	0.04	0.01	0.18	0.02	0.01
WOW	0.11	0.02	0.01	0.11	0.01	0.00	0.13	0.01	0.00	0.10	0.01	0.00	0.12	0.01	0.01	0.15	0.03	0.02
Avge.	0.14	0.03	0.02	0.12	0.01	0.01	0.13	0.01	0.00	0.14	0.03	0.01	0.13	0.02	0.02	0.14	0.02	0.01

20 ASX-listed stocks actively traded from January 1994 to December 1995.
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Table 4
R^2 values for OLS regressions between return and imbalance in the number of new orders placed

	Return → OI number									OI number → Return								
	Day			Day/Night			Hourly			Day			Day/ Night			Hourly		
ASX code	Incl. Ro	Excl. Ro	Excl. R	Incl. Ro	Excl. Ro	Excl. R	Incl. Ro	Excl. Ro	Excl. R	Incl. OIo	Excl. OIo	Excl. OI	Incl. OIo	Excl. OIo	Excl. OI	Incl. OI	Excl. OIo	Excl. OI
AMC	0.65	0.65	0.57	0.21	0.13	0.07	0.24	0.17	0.13	0.04	0.03	0.03	0.13	0.04	0.04	0.10	0.02	0.01
ANZ	0.48	0.48	0.36	0.37	0.28	0.22	0.41	0.33	0.29	0.03	0.03	0.02	0.16	0.04	0.03	0.13	0.02	0.01
BHP	0.77	0.76	0.67	0.47	0.42	0.31	0.55	0.52	0.48	0.06	0.02	0.02	0.13	0.05	0.03	0.08	0.01	0.01
BOR	0.80	0.80	0.76	0.50	0.43	0.38	0.53	0.47	0.45	0.04	0.03	0.02	0.18	0.08	0.06	0.15	0.05	0.05
CBA	0.81	0.81	0.76	0.53	0.46	0.40	0.59	0.55	0.52	0.04	0.04	0.04	0.16	0.04	0.04	0.13	0.02	0.01
CML	0.32	0.32	0.26	0.22	0.15	0.11	0.27	0.22	0.19	0.02	0.02	0.01	0.12	0.05	0.04	0.11	0.05	0.03
CRA	0.12	0.09	0.07	0.07	0.02	0.01	0.07	0.02	0.01	0.07	0.04	0.03	0.09	0.03	0.03	0.07	0.02	0.01
CSR	0.45	0.44	0.32	0.21	0.13	0.08	0.22	0.16	0.13	0.04	0.03	0.02	0.13	0.04	0.02	0.10	0.04	0.03
GIO	0.73	0.73	0.64	0.43	0.38	0.31	0.40	0.35	0.31	0.03	0.01	0.00	0.12	0.04	0.03	0.11	0.03	0.02
MIM	0.65	0.65	0.60	0.42	0.38	0.31	0.38	0.34	0.31	0.02	0.02	0.02	0.10	0.03	0.02	0.07	0.02	0.01
NAB	0.70	0.70	0.63	0.47	0.36	0.28	0.51	0.44	0.40	0.04	0.04	0.03	0.20	0.03	0.01	0.14	0.02	0.01
NBH	0.46	0.46	0.35	0.20	0.14	0.09	0.20	0.13	0.11	0.03	0.03	0.01	0.10	0.02	0.02	0.08	0.01	0.01
NCM	0.23	0.21	0.12	0.16	0.10	0.07	0.11	0.05	0.03	0.07	0.05	0.03	0.11	0.03	0.02	0.08	0.01	0.01
NCP	0.45	0.44	0.40	0.23	0.14	0.08	0.22	0.17	0.13	0.03	0.02	0.01	0.12	0.02	0.01	0.07	0.01	0.01
PDP	0.84	0.84	0.83	0.64	0.60	0.58	0.66	0.63	0.62	0.02	0.02	0.02	0.12	0.03	0.03	0.09	0.02	0.01
SRP	0.51	0.50	0.48	0.25	0.20	0.18	0.25	0.19	0.17	0.03	0.02	0.02	0.09	0.03	0.03	0.10	0.03	0.03
STO	0.46	0.45	0.39	0.23	0.17	0.13	0.24	0.18	0.15	0.04	0.03	0.02	0.09	0.03	0.03	0.10	0.03	0.03
WBC	0.45	0.44	0.32	0.30	0.18	0.11	0.23	0.16	0.13	0.04	0.03	0.00	0.17	0.03	0.01	0.11	0.02	0.01
WMC	0.51	0.51	0.41	0.28	0.22	0.13	0.27	0.21	0.16	0.04	0.04	0.03	0.12	0.04	0.02	0.09	0.02	0.02
WOW	0.75	0.74	0.66	0.49	0.44	0.36	0.47	0.42	0.38	0.01	0.01	0.00	0.12	0.02	0.02	0.11	0.03	0.02
Avge.	0.56	0.55	0.48	0.33	0.27	0.21	0.34	0.29	0.26	0.04	0.03	0.02	0.13	0.04	0.03	0.10	0.02	0.02

20 ASX-listed stocks actively traded from January 1994 to December 1995.
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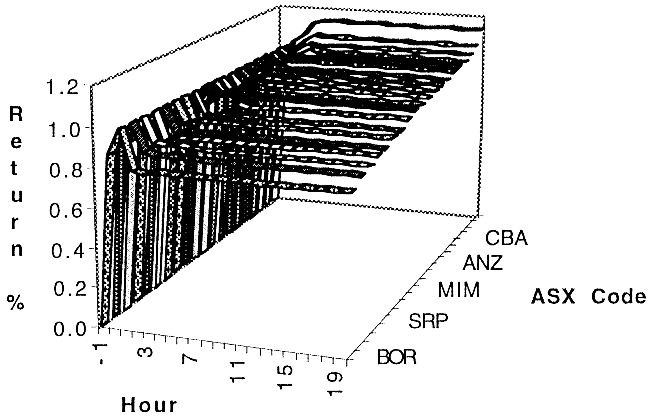

Fig. 1. Cumulative Return IRF: return innovation leading to 1% initial return, zero innovation in OI value.

ance interaction we are modelling. The initial return innovation is the value shown in period 0; the cumulative return in period 1 results from the initial innovation and the subsequent interaction between price and order flow over the first hour; and the cumulative effect on return is then traced for the next 19 periods. Similarly, Fig. 2 assumes an initial order flow innovation that leads to a $+0.167$ order imbalance over the first hour (approximately one standard deviation); an innovation of 0.167 would be consistent, for example, with a shift in order flow from equal buys and sells, to sells outnumbering buys 2 to 1. The effect of return on the interaction between order flow and return is then traced for each of the next 19 periods. Figs. 3 and 4, which trace the response of OI value to an innovation in

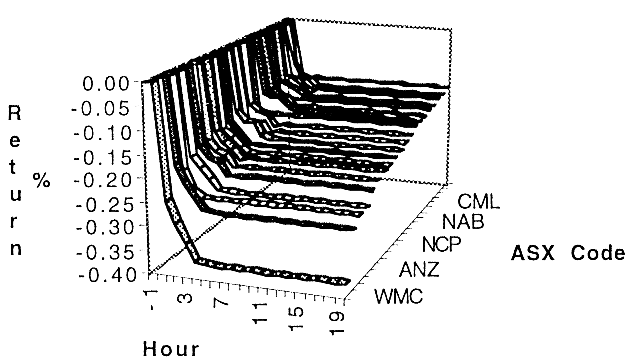

Fig. 2. Cumulative return IRF: zero innovation in return, innovation in order flow leading to initial change of 0.167 in OI value.

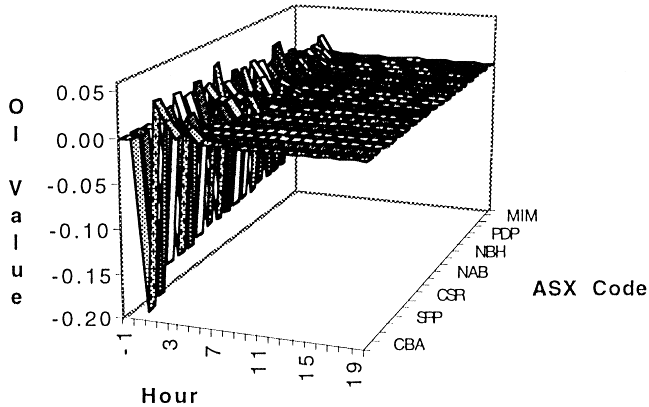

Fig. 3. OI Value IRF: return innovation leading to 1% initial return, zero innovation in OI value.

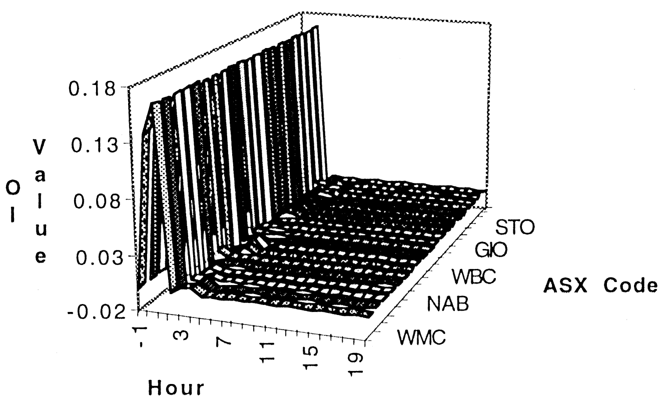

Fig. 4. OI Value IRF: zero innovation in return, innovation in order flow leading to initial change of 0.167 in OI value.

return and OI value, respectively, are generated in much the same way. The main difference is that the OI response is not cumulated over time. [11]

Figs. 1 and 4 give the impulse response functions (for return, the cumulative IRF) for impulses in themselves. While this does not examine the sensitivity and lag structure of the causal relationships we principally concentrate on, the results are still quite interesting. In Fig. 1, note that the impulse in period $(-1, 0)$ is such that the cumulative IRF is exactly 1% at the end of the period $(0, 1)$, for all

[11] Order imbalance, as we measure it, is bounded by 0 and 1; its value between two points in time, say two hours apart, is a weighted average of the two intermediate values. Since there are strong intraday patterns in order flow, these weights depend on the time of day. Consequently we do not present cumulative response functions for OI.

companies. The initial impulse ranges between 85% and 90% of the total price change that was seen. The return innovation appears to induce a further but smaller price increase in the hour following the initial impulse. In 19 of the 20 companies studied, this is then followed by a return reversal of approximately 10% of the initial impulse, but in 16 of the 20 companies, the cumulative response remains above the initial impulse. Fourteen of the 20 remain above 1%, and BHP has the largest cumulative gain of 1.14%. Interestingly, this suggests that innovations in returns take more than an hour to become fully incorporated (up to three or four hours in most cases). Further, it suggests that there is an initial over-reaction by the market, indicated by the return reversal. However, of more interest is the result that for most companies the return innovation contains ‘‘news’’ – a positive return innovation induces a non-zero positive response. This supports previous results like Walsh (1997). In Fig. 4, the size of the innovation required to induce a 0.167 impulse response at the end of period (0, 1) varies between 85% and 92% of 0.167. Note that this graph is not a cumulative impulse function. The results are uniform across companies in the sample; within two or three hours of the innovation, the effects completely die away, and the initial innovation is followed by almost no further reaction.

Figs. 2 and 3 examine the impact of innovations of one variable on the other variable. Fig. 2 gives the cumulative impulse response of return to an OI innovation that leads to a 0.167 response in OI at the end of period (0, 1). A positive impulse in OI (that is, an increase in the proportion of sell orders) leads for every company to a decrease in return, taking up to 3 hours to become fully incorporated. The total cumulative impact of this ‘‘one standard deviation’’ order imbalance impulse on return is in total between −0.14 and −0.37%. Fig. 3 shows the response of OI to an innovation that leads to a 1% initial return. Again, this is not a cumulative response. After the initial response in period (0,1), the OI reverses strongly. A positive innovation in return induces a strong buy order imbalance, followed by a strong correcting sell order imbalance, in all cases larger than the initial response. After this reversal, the OI settles down within about 3 h.

The same four graphs were generated for the interaction between return and OI number. The results are very similar, although the lag structure of OI number is different to that of OI value, producing less stable impulse response functions. [12]

6. Conclusions

Causality tests were conducted on the 20 most actively traded stocks over the two years 1994–95. Three data sets, comprising midpoint returns and imbalance in

[12] The graphs are available from the authors.

the number and value of buy and sell orders, were formed for each stock: close-to-close; close-to-open and open-to-close; and close-to-open plus the six trading hours. We found that, for an individual stock, if the contemporaneous observation of order flow imbalance (return) is included in the return (order flow imbalance) regression, causality is bi-directional. When it is excluded, the causality results change substantially: order value affects returns but the number of orders does not. Conversely, returns affect imbalance in the number and value of new orders placed.

Impulse response functions were plotted using estimates from hourly return and OI value data. We saw that an exogenous price rise typically triggers an additional but smaller rise in the first hour, followed by a partial reversal in the second hour of about a tenth of the initial innovation. Similarly, it induces a surge in the value of buys relative to sells, which is followed in the second hour by an imbalance in favour of sells. An exogenous increase in the value of sells leads to more sell orders and lower prices. In all cases the adjustment is complete within about three hours. A fair conclusion is that, on the ASX, a buy order imbalance is weakly associated with higher future prices and a sell order imbalance with lower prices. Finally, because adjustment to order imbalance appears to be within two or three hours on the ASX, imbalance in the value of new orders placed is probably driven more by information than by price stabilisation per se.

At least two clear directions of further research present themselves. First, examining cross-listed securities between exchanges would allow direct control over firm-specific effects, leaving exchange-related effects to appear in the results.[13] Second, exploring the number and size of orders as different metrics will almost certainly provide fruitful conclusions on the information content of different ''areas'' of the order flow. As we noted earlier, there is a strong informational difference between the metrics, and this will reflect in trading size and frequency.

For further reading, see (Aitken et al., 1993; Glosten and Milgrom, 1985; Lease et al., 1991; Lee et al., 1993).

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[13] A referee drew this point to our attention.

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