Calling the end of the bubble: are there trends in order imbalances?

There are numerous pundits predicting the end of the stockmarket bubble but getting the timing right is another matter. **JULIA HENKER** and **THOMAS HENKER** make the case that careful scrutiny of trader activity may provide a clue.

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Can traders effectively conceal their information processing from the rest of the market, or is it there for the alert investor to observe? Could we see, for example, the reduction in demand that leads to the crash of a stock price bubble, or can investors keep their sentiment private?

We might expect that if we look carefully at buy and sell orders over several days, we could forecast the change from an upward to a downward trend in asset prices, but we would be wrong.

In this article, we investigate whether stock price bubble crashes are foreshadowed in order imbalances. Uninformed investors, lacking any better means, could try to anticipate price changes based on demand and supply, particularly in a limit order market like the Australian Securities Exchange (ASX).

Experimental (Smith, Suchanek and Williams, 1988) and empirical (Henker and Owen, 2006) studies suggest that the one period lagged order imbalance is correlated with asset price changes. However, whilst professionals react quickly, most amateur investors would require a trend of several periods to induce them to act. We find that markets do not provide that trend.

The tendency of people to follow trends is a favourite heuristic of behavioural finance theorists (Shiller, 2000). In 1993, and again in 2001, Jegadeesh and Titman showed that profits could be made by simply buying stocks that had performed well in the past and selling those that performed poorly (Jegadeesh and Titman, 1993, Jegadeesh and Titman, 2001). Grinblatt, Titman and Wermers (1995) include herding, the tendency to copy the trades of other investors, in their discussion of momentum and mutual funds. Herding is a way for uniformed investors to trade on the knowledge of others. However, as Chakravarty (2001) shows, informed traders are skilled at hiding their opinions from the market, concealing large quantity trades as a series of smaller, less salient transactions.

HIDING INFORMATION

We show that traders are also skilled at hiding the information in their unmet demand, thwarting observers hoping for a prediction of the end of a stock price bubble. Though researchers may debate the existence of stock price bubbles (Garber, 2000, Siegel, 1998), investors not only acknowledge them [Fisher and Statman (2002)], but appear to use bubble patterns to achieve excess returns (Brunnermeier and Nagel, 2004).

Successfully exploiting a market bubble requires accurately predicting the crash. Move too soon and profit is left on the table; wait until after the bubble breaks and realise losses.

At issue here is not the investor's private opinion of the value of the stock, in fact, the belief that the asset is experiencing a bubble is tantamount to stating that the asset is overpriced. Rather, to borrow a concept from Keynes (1936), the issue is to ascertain when other investors will consider the asset overpriced and beat them to the sale.

The exercise is made even more complicated by the fact that many asset bubbles burst in spite of there being no obvious new information about the individual securities or the economy in general. Theory argues against the extended presence of information in order imbalance numbers. Hart and Tauman (2004) propose a theory of information processing that allows for sudden market changes in absence of external, or exogenous, information. They argue that traders with different sets of information can refine their knowledge by monitoring one another's trades.

However, this process of converting "common knowledge", i.e. prices and quantities traded, to "mutual knowledge", that is, shared expectations that certain events will occur, is not observable. Traders' behaviour remains stable for some arbitrary length of time and then suddenly changes. In the words of Hart and Tauman (2004), "Market crashes (and, similarly, market bubbles) may well be the result of information processing by the participants — and nothing else. Moreover, in terms of market observables, it looks as if nothing is really changing. Still, underneath the surface, there is a gradual updating of information by the participants. Then, at a certain point in time, this causes a sudden change of behaviour". (p.1)

IDENTIFYING BUBBLES

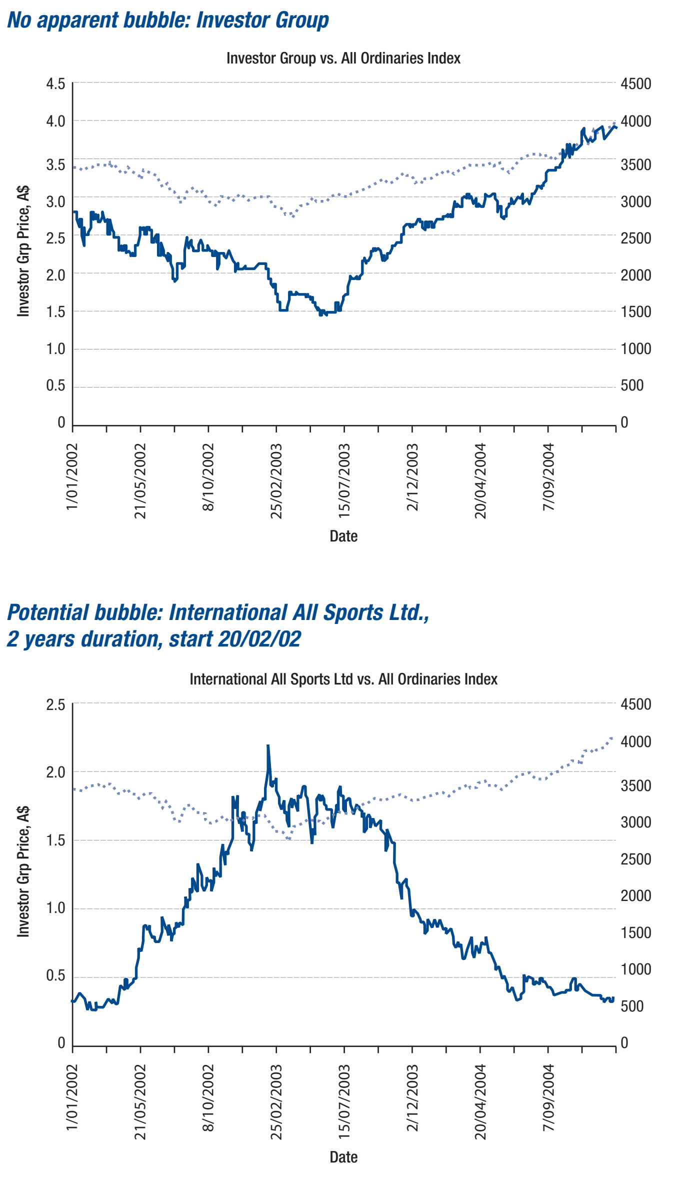
To identify shares experiencing a price bubble, the first step in exploring the question of whether the information processing happens covertly or as an observable trend, we follow the procedure detailed in Henker and Owen (2006).

Briefly, we look for a specific price pattern in which share prices, adjusted for stock splits, share repurchases and related activities, increase dramatically for a period of time and subsequently revert to lower levels. We do so by graphing price data for each of the approximately 500 companies in the Australian All Ordinaries index over a 20-year period ending in December 2003 and compare them to the price pattern of the index for the same period.

A 'potential bubble' is a pronounced and persistent deviation from the index pattern which subsequently reverses. Figure 1 illustrates an example of a pattern identified as a 'potential bubble' stock and of one not considered for the initial sample. We add confidence to our data sample selection with a series of standard econometric tests[1] for deviation of stock prices from fundamental stock value.

With these criteria, we identify a sample of 83 Australian companies that experience a stock price bubble. The sample encompasses a range of industries, though technology companies represent about a third of the total. The majority of the companies are fairly small, with average market capitalizations of less than A$1 billion, but the sample also includes several of the largest companies on the ASX.[2]

FIGURE 1 **SAMPLE OF BUBBLE IDENTIFICATION GRAPHS**



To establish an objective measure of the duration of the bubble, we anchor, for each company, on the day on which the highest price is achieved. We sort the companies into six groups by the approximate duration of their price deviation; the groups comprise bubbles with a duration of up to three months, three to six months, six to 12 months, 12 to 24 months, 24 to 36 months and 36 to 60 months. Data are then collected for each company equal to the maximum duration of its group centered on the highest price achieved during the deviation from fundamental value.

For example, for each stock in the up-to-three-month category, we include data from six weeks before the peak to six weeks after the peak, and so on.[3]

The stock price and order data are collected from the Stock Exchange Automated Trading System (SEATS) of the Australian Securities Exchange (ASX), distributed by the Securities Industry Research Centre of Asia-Pacific (SIRCA).

For each company we acquire close of trade (16:00) data, including last traded price, dividend distributions, all valid bid order prices and volumes and all valid ask order prices and volumes.

We calculate several order imbalance indicator variables. Our first indicator considers the volume of bids minus asks, a measure we compare to bubble stock price changes. To investigate the relation of order imbalance to stock returns, a relative value, we use Equation (2) to compute a relative order imbalance indicator:

$$ret_{i,t} = \frac{price_{i,t} + dividend_{i,t}}{price_{i,t-1}} - 1, \forall i \qquad (1)$$

$$relBMAvol_{i,t} = \frac{Bvol_{i,t} - Avol_{i,t}}{Bvol_{i,t} + Avol_{i,t}}, \forall i \qquad (2)$$

The subscript i indicates the individual stock, while t indicates a specific day. $Bvol_{i,t}$ ($Avol_{i,t}$) denotes the total volume of bid (ask) orders for stock i at the close of day t. These imbalance indicators are our measure of demand for the bubble stocks.

However, since our data are limit orders, we consider the possibility that the market price may move away from the order price. Although the ASX invalidates orders that are too far from the current market price,[4] stale but still valid orders may unduly influence our measure of excess demand. Accordingly, we refine our order balance measure further using the price weighting factors as in Henker and Owen (2006):

$$bidwt_{j,i,t} = 1 - \left[\frac{(bestbid_{i,t} - bid_{j,i,t})}{(bestbid_{i,t} + bid_{j,i,t})}\right] \qquad (3)$$

$$askwt_{j,i,t} = 1 - \left[\frac{(bestask_{i,t} - ask_{j,i,t})}{(bestask_{i,t} + ask_{j,i,t})}\right] \qquad (4)$$

where $bestbid_{i,t}$ ($bestask_{i,t}$) is the highest (lowest) order price for stock i at time t, and $bid_{j,i,t}$ ($ask_{j,i,t}$) refers to a specific order j for stock i at time t. Equations (3) and (4) result in a number between zero and one that is smaller the further the quote is from the best quote. These weighting factors retain all of the demand information in the order book while acknowledging that quotes further from the best quote exert less price pressure. We use these factors and the following formulae to calculate weighted volumes.

$$wtBvol_{i,t} = \sum_j bidwt_{j,i,t} * volume_{j,i,t} \qquad (5)$$

$$wtAvol_{i,t} = \sum_j askwt_{j,i,t} * volume_{j,i,t} \qquad (6)$$

That is, to compute the weighted bid (ask) volume at time t, we multiply the volume associated with bid (ask) order j by $bidwt_{j,i,t}$ ($askwt_{j,i,t}$) and add the weighted volumes for all orders for each stock i at time t. The weighted relative imbalance indicator variable is determined with Equation (7).

$$relwtBMAvol_{i,t} = \frac{wtBvol_{i,t} - wtAvol_{i,t}}{wtBvol_{i,t} + wtAvol_{i,t}}, \forall i \qquad (7)$$

Thus, $relwtBMAvol_{i,t}$ is the total price-weighted volume of bid orders for stock i at time t minus the total price-weighted volume of ask orders for stock i at time t standardised by the sum of the price-weighted volume of bid and ask orders for stock i at time t. (*BMA* denotes 'bid minus ask.')

These manipulations result in four measures of order imbalance: the unweighted and the weighted difference in volume of bid and ask orders and the weighted and unweighted relative volume difference indicators. Table 1 summarises the raw data as well as the weighted and unweighted total volume variables. The weighting factor deflates both the bid and the ask volumes by about 8.5%, reducing the impact of orders at prices further from currently traded prices.

The average daily return is very slightly positive, but not statistically significantly different from zero. Given the way we define our sample as a dramatic price increase followed by an equally dramatic fall, and the non-symmetry of returns,[5] a small positive return is to be expected.

The average ask order volume is considerably larger than the average bid order volume; accordingly the average order imbalance is negative. This unintuitive result calls for some discussion. These data are unfilled buy and sell orders over the entire period of the bubble. We might expect excess buy demand over the bubble growth period to closely offset

TABLE 1 **SUMMARY STATISTICS**

Variable	Mean	Standard deviation	Range (average min to average max)
Number of observations	618	434	57 to 1440
Price (A$)	4.63	1.92	1.53 to 9.33
Return (%)	0.135	0.06	-44.9 to 49.9
Total bid volume (000s)	462.4	411	45.8 to 3216.4
Weighted bid volume (000s)	422.8	369.9	46.1 to 2972.1
Total ask volume (000s)	707.8	541.9	69.8 to 3660.3
Weighted ask volume (000s)	647.8	497.1	66.7 to 3480.1
Total bid volume minus total ask volume (000s)	-245.6	581.1	-3011.7 to 2503.0
Weighted bid volume minus weighted ask volume (000s)	-224.7	517.1	-2867.5 to 2245.1

The table presents summary statistics for the variables in the first column, averaged over the 83 stocks included in the sample.

excess sell demand over the crash period.

However, if it is generally believed that a stock is experiencing a price bubble, as the survey results of Fisher and Statman (2002) show is quite possible, the stock is overpriced. Fundamentals investors or "arbitrageurs" are quite eager to sell or short sell overpriced stocks.

These investors meet some of the buy demand during the growth period, reducing the volume of unfilled purchase orders. During the crash phase of the bubble, all investors, fundamental as well as trend following, will try to sell, inflating the volume of unfilled sell orders.

Testing for trends

Henker and Owen (2006) use regressions to show that changes in the imbalance measure reliably predict changes in the next day's price or return. Our goal with this paper is to investigate whether we can identify a trend in these indicator variables during the course of the stock price bubble.

We want to determine whether traders update their information over several days in full view of the market, or whether, as Hart and Tauman (2004) theorise, the updating occurs outside the range of observable order imbalance measures. We do so by asking whether additional lagged values of the imbalance measures add predictive power to the price change models.

We test the following models for each of the bubble stocks. Equation (8) tests order imbalance over one week of data, expressed as the difference between the volume of unweighted bid and ask orders against price changes, while Equation (9) considers the same, except the volume of bid and ask orders is weighted by their price. Equations (10) and (11) investigate the relation over one week of unweighted and weighted relative order imbalance (respectively) and returns.

The variable *pt* is the price of the individual stock on day *t*, while *Bvolt-n (Avolt-n)* is the total volume of all bid (ask) orders on day *t-n*. The other variables are as calculated with the previous equations.

TABLE 2: RESULTS OF REGRESSIONS WITH MULTIPLE LAGS

Panel A: Unweighted $$p_t - p_{t-1} = \alpha + \sum_{n=1}^{5} \beta(Bvol_{t-n} - Avol_{t-n}) + \varepsilon_t, \forall i$$

Number of coefficients significant at specified level	*lag length*				
	one lag	two lags	three lags	four lags	five lags
1%	28	5	2	2	0
1%<X<5%	14	7	3	5	3
5%<X<10%	4	7	2	5	8
Total significant/ 83	46	19	7	12	11

Panel B: Weighted $$p_t - p_{t-1} = \alpha + \sum_{n=1}^{5} \beta(wtBvol_{t-n} - wtAvol_{t-n}) + \varepsilon_t, \forall i$$

Number of coefficients significant at specified level	*lag length*				
	one lag	two lags	three lags	four lags	five lags
1%	29	4	3	2	0
1%<X<5%	15	8	1	5	4
5%<X<10%	4	8	2	5	8
Total significant	48	20	6	12	12

Panel C: Unweighted relative $$ret_t = \alpha + \sum_{n=1}^{5} \beta(relBMAvol_{t-n}) + \varepsilon_t, \forall i$$

Number of coefficients significant at specified level	*lag length*				
	one lag	two lags	three lags	four lags	five lags
1%	53	8	5	2	4
1%<X<5%	4	11	5	5	4
5%<X<10%	5	6	9	6	10
Total significant	62	25	19	13	18

Panel D: Weighted relative $$ret_t = \alpha + \sum_{n=1}^{5} \beta(relwtBMAvol_{t-n}) + \varepsilon_t, \forall i$$

Number of coefficients significant at specified level	*lag length*				
	one lag	two lags	three lags	four lags	five lags
1%	52	8	5	2	4
1%<X<5%	4	11	5	5	5
5%<X<10%	7	6	9	6	8
Total significant	63	25	19	3	17

This table summarises the results of the regressions with multiple lags, i.e., Equations (8–11), with weighted and unweighted imbalance variables. Each panel summarises the regression specified at the top of the panel. The numbers in the table represent the number of companies (out of the sample of 83) for which the coefficient for the lag identified in the column is significant at the level identified in the row.

$$p_t - p_{t-1} = \alpha + \sum_{n=1}^{5} Bvol_{t-n} - Avol_{t-n} + \varepsilon_t,\ \forall i \qquad (8)$$

$$p_t - p_{t-1} = \alpha + \sum_{n=1}^{5} wtBvol_{t-n} - wtAvol_{t-n} + \varepsilon_t,\ \forall i \qquad (9)$$

$$ret_t = \alpha + \sum_{n=1}^{5} relBMAvol_{t-n} + \varepsilon_t,\ \forall i \qquad (10)$$

$$ret_t = \alpha + \sum_{n=1}^{5} relwtBMAvol_{t-n} + \varepsilon_t,\ \forall i \qquad (11)$$

In Table 2 we summarise the results of the individual regressions. We report the number of significant coefficients of the lagged excess demand variables from Equations (8–11). We do not find a trend in the order imbalances, even with the refined indicators. Although some of the coefficients of the additional lags are significant for individual stocks, the significance is scattered, with no apparent pattern of useful information. The number of coefficients significant at the 1% level for one lag is, on average, 6.5 times as large as the number significant for two lags, and fewer estimates are significant for the additional lags. We conclude that the additional lags are not useful in consistently predicting future price changes.

This result is consistent with the theory proposed by Hart and Tauman, and not with the idea that there is a discernible trend in the order imbalance indicators.

The theory argues that updating of expectations can occur in the market without being reflected in market observables, like our order imbalance variable. A change, when it occurs, may then appear to be sudden even though it has been slowly filtering through the market. Our test of one market observable, that of order imbalance, suggests that there is no reliable indication in the level of the observable for two through five days before the event.

We do find, consistent with the results of Henker and Owen (2006), that the modified order imbalance variables are superior predictors to the simplest one. Weighting orders by their distance to the traded price and then transforming the imbalances into relative imbalances improves the power of the model to predict price changes. In the simplest model, Panel A of Table 2, the first lagged imbalance is a statistically significant predictor (at the one per cent level) of future price changes for 28 of the 83 stocks. After modifications, results reported in Panel D, the performance improves to 52 of the 83 stocks, nearly doubling the number of coefficients significant at the one per cent level. For all significance levels, the one-day lagged weighted relative imbalance indicator (Panel D) is a significant predictor of price changes for 75% of the sample; the two-day lag generates significant predictors only 30% of the time, and subsequent lags are even less successful.

IMPLICATIONS

Informed traders in the Australian market successfully conceal their changing demand for stocks experiencing price bubbles. Predicating trading on order imbalances observed over several days for stocks experiencing a stock price bubble in the Australian market does not yield consistently useful information about future stock price changes. Only the order imbalance one day prior contains useful information about price changes on the following day.

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Notes

1 Specifics of the econometric tests are available from the authors. The tests eliminated four companies from the sample identified with the graphs.

2 More information about the companies in the study is available from the authors.

3 There is some slight variation in this procedure caused by practical matters. For example, adjustments are made for companies that start up or are de-listed or acquired during the window. Trading halts, suspensions and holidays also affect the total number of observations for some companies.

4 How far is “too far” from the market price is a function of the price of the stock? At time of writing, the security price ranges and order purge prices, respectively were as follows: AUD 0.001 to 0.099, 0.10; 0.10 to 0.495, 0.50; 0.50 to 4.99, 0.50; 5.00 to 29.99, 2.00; 30.00 to 249.99, 5.00; 250.00 to <999.99, 50.00. www.asx.com.au

5 That is, for example, an increase from $1 to $2 would be a 100% gain, while a decrease from $2 to $1 is only a 50% loss.

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