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Bursting Bubbles: Linking Experimental Financial Market Results to Field Market Data

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The laboratory, where variables can be measured and controlled, is perhaps the most efficient place to test scientific theory, yet in general empirical financial research neglects experimental finance results. We link laboratory findings to actual, or field, data, applying the Smith, Suchanek and Williams [1988] experimental market model to Australian stock exchange data. We introduce modifications that improve the model's fit to field market conditions. The experimental model is a reliable predictor of field market bubble bursts in more than 50% of the cases we test, and our modifications improve the performance to 77% of the cases. Our results suggest that experimental financial market results should be accorded more attention in empirical research.

INTRODUCTION

By the early 2000s, the new economy of the 1990s had proven itself to be just another old-fashioned asset price bubble. Many investors were not surprised there was a bubble, nor that it eventually burst. Fisher and Statman [2002] cite separate surveys of individual and institutional investors, asserting that both investor types believed that the market was overvalued in the late 1990s. However, the two groups did not agree on a prognosis for the bubble. Individual investors believed that the bubble would continue to grow, while institutional investors were bearish.

Although identification of asset price bubbles in field markets is subjective, asset price bubbles can be clearly identified in the controlled environment of the laboratory. Caginalp, Porter and Smith [2000] summarize a variety of laboratory experiments, finding that the "bubble-and-crash behavior is robust to variations in a number of variables, including liquidity, short-selling, certainty or uncertainty of dividend payments, brokerage fees, capital gains taxes, buying on margin, and others" (p. 24). They propose a momentum model and compare it to the excess bid model of Smith, Suchanek and Williams [1988], finding that the latter model has a slightly better one period performance.

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We apply the Smith, Suchanek and Williams [1988] (SSW) model to actual market data and introduce several modifications to improve its fit with real market conditions. We find that the experimental model is a reliable predictor of field market bubble bursts in more than 50% of the cases we test. Our modifications improve the performance to 77% of cases. Our results suggest that experimental results can be applied to field markets and that investors can get useful information about impending asset bubble price crashes from observing the entire order book.

The balance of the paper is organized as follows. In the next section, we discuss our hypotheses and the relevant previous literature. Following that, we introduce our data source and selection procedure, with a brief discussion of the econometric tests we use to identify field market bubbles. The fifth section introduces the variations of the model. We present our results in section six and conclude in section seven.

LINKING EXPERIMENTAL RESULTS TO FIELD DATA

Our primary goal in this paper is to adapt an experimental financial market model to field market data. Some empiricists dismiss laboratory markets as too simple to provide insight into the mechanism of field markets. However, the ability to control various aspects of the laboratory markets enables researchers to consider questions that would otherwise be intractable. Caginalp, Porter and Smith [2000] summarize a series of experiments that incorporate insiders, experience, professionals, futures markets, price limits and other features of asset markets. Asset price bubbles occur in all of these experimental markets, albeit with varying amplitudes. They conclude that the excess bids model is consistently the most reliable predictor of the reversal in price growth trends. Interestingly, the very traders whose activity causes the reversal are not reliable forecasters of price changes. Smith, Suchanek and Williams [1988] study forecasting behavior, finding that forecasts are more closely related to past forecast error than to future prices. Moreover, "the forecasts under-predict in the boom phase and over-predict in the crash" (p.1149).

We hypothesize that a similar relation between excess demand and price change exists in field markets. However, even with the features discussed by Caginalp, Porter and Smith [2000], the laboratory environment differs considerably from that of field markets. We introduce modifications to the SSW model to address the following differences between field and laboratory markets: experimental market volume is comparatively low, there is often only one risky traded asset, fewer factors determine the fundamental value of the asset and the number of trading periods is limited and known to participants.

Asparouhova, Bossaerts and Plott [2003], responding to suggestions from practitioners that "the relative thickness of the two sides of the book provides useful information to gauge the direction of the markets if change is to take place" (p. 19), calculate a volume-weighted price. We incorporate the practitioners' suggestion in the opposite manner. In an order-driven market such as the Australian Stock Exchange (ASX), the market price may move far away from a limit order price, particularly for volatile stocks. These distant orders, while valid, are not as important an indicator of current supply and demand as are closer orders. Thus we weight the volume of each order by its price proximity to the best order. That is, using all of the valid quotes, we construct a quote-weighted average volume of bids and of asks (see Equations 2 and 3 in the fifth section). The difference between these weighted average volumes is our indicator of excess demand. As illustrated in Table 2 of the sixth section, this weighting factor improves model's performance.

The excess demand model introduced in Smith (1962) features absolute price changes. In an experimental market, where trading lasts perhaps 15 periods and dividend payments are relatively small, the price of the risky security will move within a limited range. However, the perceived infinite potential of stocks in field markets can result in absolute inter-period price changes that range from a few cents to several dollars over the interval of the bubble. To mitigate the effect of this broad range, we convert the absolute price change to relative price change, or return. Previous studies have considered the relation between price change and excess demand in the context of price discovery with various measures.[1] To remain consistent with an excess demand model, we calculate our standardized order imbalance variable as the (weighted) volume of bids minus the (weighted) volume of asks divided by the sum of the (weighted) volume of bids plus (weighted) volume of asks (see Equations 6 and 7).

Smith, Suchanek and Williams [1988] also observe that the crash in market prices occurs on lower order volume than that which prevailed during the boom. We test our field market data, using both unweighted and weighted volumes, for a similar relation. However, in the laboratory the end of trading and the expected value of the liquidating dividend are known to all market participants. In field markets, investors often believe they can wait for the price to recover to its former levels, as evidenced by the Odean [1998] finding that the individual investors exhibit the 'disposition effect.' Therefore, we expect to find that bid volume after the peak is lower than before, but ask volume is not, or that it decays much more slowly. However, since inflated ask order volume caused by investors waiting for prices to recover does not translate into inflated transaction volume, we expect transaction volume to be reduced in line with experimental market observations.

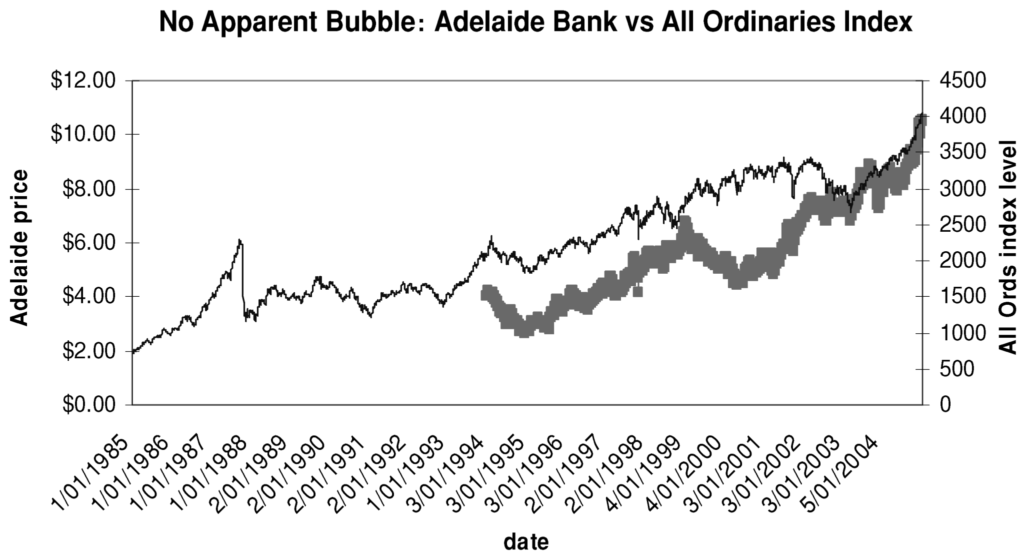
Our study links experimental and empirical finance. We find that results from the laboratory can be applied to field markets and we improve the performance of the experimental market model by modifying the variables to better reflect field market characteristics. Our modifications include weighting orders by their proximity to the best order, considering relative rather than absolute changes and including additional tests to account for the extra variability of field markets. We find the same excess demand-price change relations in field markets, and our modifications improve the relation.

DATA

Identification of Bubble Stocks

To test the results from experimental financial markets, we must first identify asset price bubbles in field data. In field markets, defining a bubble is problematic. Various price to fundamental ratios are common measures of overvaluation, but the use of these ratios relies on context; no statements about overvaluation can be made by comparing, for example, the price to earnings (P/E) ratio of a growth company with that of a value company.[2]

Our primary data requirement is to find bubbles that have collapsed. As a result, we look for companies whose share price, adjusted for stock splits, share repurchases and related activities, increases dramatically for a period of time and subsequently reverts to lower levels, consistent with a definition of asset price bubbles specified by Kindleberger [1978]. To identify bubble candidates, we graph price data for each of the approximately 500 companies in the Australian All Ordinaries index over a 20-year period ending in December 2003. The graphs are compared to the price pattern of the index for the same period. We define a 'potential bubble' as a pronounced and persistent deviation



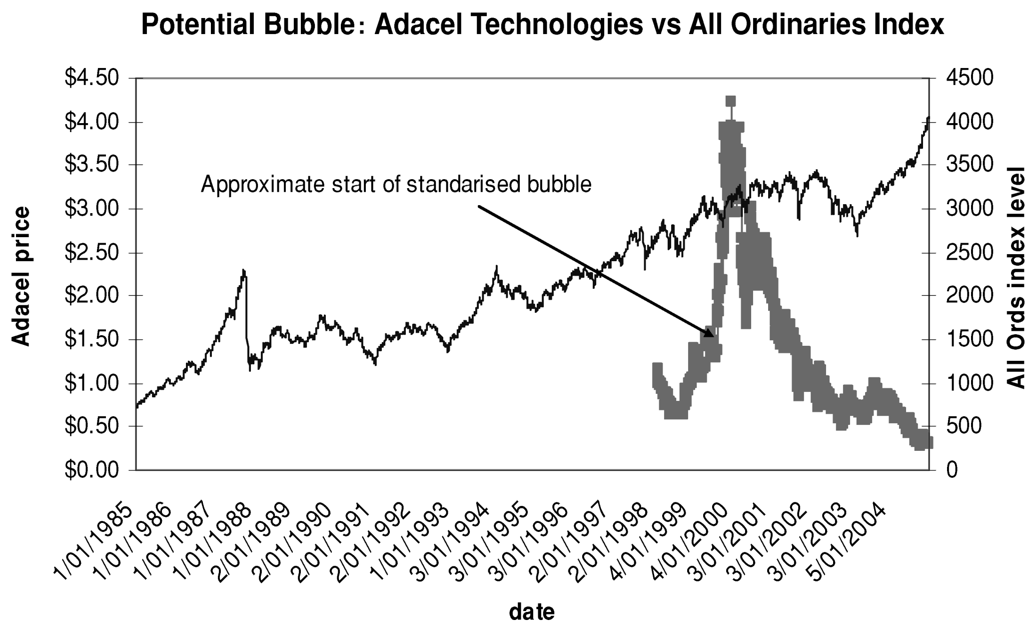


FIGURE 1 Examples of "potential bubble" identification graphs no apparent bubble: adelaide bank

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. To avoid mispricings associated with initial public offerings, we remove all observations in which the bubble occurs immediately (within one week) of the start of the data series. Of course, the potential bubble pattern is consistent with non-bubble anomalies, but these may also represent a deviation from fundamental value. Moreover, we add confidence to our data sample selection with a series of econometric tests, briefly discussed in the fourth section.

With these criteria, we identify a sample of 83 Australian companies. 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[3], but the sample also includes several of the largest companies on the ASX.[4]

Another practical challenge is to decide on an objective measure for the period of the bubble. Even with a clear bubble pattern, without knowledge of the true fundamental value of an asset, pinpointing the starting and ending dates of the deviation is subjective. However, the day on which the highest price is achieved can be identified precisely. We sort the candidate companies into six groups by the approximate duration of their price deviation; up to 3 months, 3–6 months, 6–12 months, 12–24 months, 24–36 months and 36–60 months. We collect data for each company based on the maximum duration of its group centered on the highest price achieved during the deviation. 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.[5]

The data come from the Stock Exchange Automated Trading System (SEATS) of the 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 price and volumes and all valid ask order price and volumes. The decision to sample the data at close of trade considers the market structure and the requirements of the study. The prices and orders valid at 16:00 could have been executed in continuous trading, and are therefore not influenced by the ASX's closing single auction price. Nor are they part of a day trading speculative or liquidity provision strategy.[6] The opening of the ASX is staggered, but trading in all securities closes at the same time. Moreover, our goal of using demand to forecast next day price changes argues for using the closing bid/ask schedule rather than the opening one, which would be expected to impact the concurrent day.

Econometric Tests for Bubbles

Econometric tests for asset price bubbles attempt to identify a structural change in the price series that could be attributed to a break from fundamental value. The seminal work in this field is Blanchard and Watson [1982], who propose a battery of statistical tests to identify abnormal behavior in the price series. They first test the price series for excess kurtosis and positive skewness. Next, they look for consecutive observations with the same sign, or runs, in the excess returns in the series. In a stock price bubble there will be far fewer runs than would be expected in a random distribution, and these runs will be of considerably longer duration. These initial bubble tests are, however, of limited power in that the characteristics they identify can be attributed to other anomalies as well as asset price bubbles.

More recently, tests for bubbles have been developed that use Markov switching models. While van Norden and Vigfusson [1996] advocate a two regime model, Brooks and Katsaris [2005] use a three regime model to allow for a period of constant growth in addition to the standard growth and burst phases. Because of the standard intervals we impose in our sample selection method, we may include intervals longer than an individual stock's price bubble. Therefore, we follow Brooks and Katsaris [2005] and estimate three regime Markov switching models to allow for a possible non-bubble phase. We use a simple time series for the underlying model specification as in Blume, MacKinlay and Terker [1989]. Four of the original 87 potential bubble companies fail to satisfy these econometric tests and are removed from consideration.

PRICE AND ORDER IMBALANCE MODELS

Models and Variations

Our objective is to test experimental market results with field data. We begin with the following SSW model of excess bids:

$$p_{i,t} - p_{i,t-1} = \alpha_i + \beta_i(B_{i,t-1} - O_{i,t-1}) + \varepsilon_{i,t}, \forall i \tag{1}$$

where p is the price of the risky traded asset, B is the total number of orders to buy the stock, O is the total number of orders to sell the stock, i is the specific stock and t is the trading interval. SSW find that this model is a very effective predictor, that is, a negative value of the independent variable is significantly correlated with a negative change in the price, in experimental trading rooms.

In experimental markets, orders are typically placed for a single unit of the risky asset. The number of bid and ask orders is a measure of the number of traders willing to buy or sell at specific prices. We test the same measure with our field market data. In field markets, however, orders are typically placed for multiples of shares. In economic terms, a single trader willing to buy ten shares at a specific price represents the same demand as ten traders willing to buy one share at the same price. Therefore, we also test Equation (1) substituting total bid (ask) volume for quantity of bid (ask) orders by substituting $Bvol_{t-1}(Ovol_{t-1})$ for $B_{t-1}(O_{t-1})$ in the equation.

Our next modification acknowledges that in experimental markets the risky security trades for a limited number of periods and terminates with a liquidating dividend, while the life of a stock in field markets is theoretically infinite. Limit buy (sell) orders placed below (above) the current market price may persist for long periods in field markets. Depending on instructions from the investor and rules applied by the broker, an order may remain valid until it is executed, or until the company announces some change that systematically affects share price or until the expiration of some predetermined length of time.[7] The market price may move away from the order price during this period of validity. Although the exchange invalidates orders that are too far from the current market[8], stale but still valid orders may unduly influence our measure of excess demand. To address this issue, we introduce the following weighting factor:

$$bidwt_{j,i,t} = 1 - \left[\frac{(bestbid_{i,t} - bid_{j,i,t})}{(bestbid_{i,t} + bid_{j,i,t})}\right] \tag{2}$$

$$askwt_{j,i,t} = 1 - \left|\frac{(bestask_{i,t} - ask_{j,i,t})}{(bestask_{i,t} + ask_{j,i,t})}\right| \tag{3}$$

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 for stock i at time t. To calculate 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. We assign the resulting weighted total bid (ask) volume the symbol $wtBvol_t$ ($wtOvol_t$).

The fractions in Equations (2) and (3) produce a value between zero and one that is larger the further the quote is from the best quote. This value is then subtracted from one, resulting in a number between zero and one that is smaller the further the quote is from the best quote. By considering all valid orders, our weighting factor retains all of the demand information in the order book. However, in weighting the volume of each order by its proximity to the best order, our weighting factor acknowledges that quotes further from the best quote exert less price pressure. Thus, we estimate the following variant of the SSW model:

$$p_{i,t} - p_{i,t-1} = \alpha_i + \beta_i(wtBvol_{i,t-1} - wtOvol_{i,t-1}) + \varepsilon_{i,t}, \forall i \tag{4}$$

Another difference between field and experimental markets is the larger size and higher volatility of the prices and volumes in field markets. The price of a representative company in our sample changes dramatically over the period under scrutiny. As a result, absolute price change, the experimental dependent variable, is a suboptimal measure. We substitute percent increase, that is, return, for the dependent variable price change and perform a similar transformation on the volume variable. Our transformations are as follows:

$$ret_{i,t} = \frac{price_{i,t} + dividend_{i,t}}{price_{i,t-1}} - 1, \forall i \tag{5}$$

$$relBMA_{i,t} = \frac{B_{i,t} - O_{i,t}}{B_{i,t} + O_{i,t}}, \forall i \tag{6}$$

$$relBMAvol_{i,t} = \frac{Bvol_{i,t} - Ovol_{i,t}}{Bvol_{i,t} + Ovol_{i,t}}, \forall i \tag{7}$$

$$relwtBMAvol_{i,t} = \frac{wtBvol_{i,t} - wtOvol_{i,t}}{wtBvol_{i,t} + wtOvol_{i,t}}, \forall i \tag{8}$$

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 standardized by the sum of the price-weighted volume of bid and ask orders for stock i at time t.[9] In addition to Equations (1) and (4), we estimate the following models for each company i:

$$ret_{i,t} = \alpha_i + \beta_i(x) + \varepsilon_{i,t}$$

$$x \in \{relBMA_{i,t-1}, relBMAvol_{i,t-1}\}, \forall i \tag{9}$$

$$ret_{i,t} = \alpha_i + \beta_i(relwtBMAvol_{i,t-1}) + \varepsilon_{i,t}, \forall i \tag{10}$$

Volume

Next we use a difference of means test to investigate our hypotheses that bid order volume after the peak is lower than before, but ask order volume is not (or decays much more slowly) and that transaction volume is lower after the peak than before. We divide the bubble sample into two periods, the interval up to and including the peak price achieved and the interval after the peak price.[10] We then calculate the test statistic defined in Equation (11) for the difference between two population means with potentially unequal variances. Critical values are obtained from t distribution tables. We use pre-peak bid volume (ask volume, transaction volume) means and standard errors for x_1 and s_1, respectively, and post peak bid volume (ask volume, transaction volume) means and standard errors for x_2 and s_2. Since pre-peak volumes should be higher than post peak, this statistic should be positive, and we employ a one tailed test.

$$t = \frac{(\overline{x}_1 - \overline{x}_2)}{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^{\frac{1}{2}}}, \forall i \tag{11}$$

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{\left(s_1^2/n_1\right)^2}{n_1} + \frac{\left(s_2^2/n_2\right)^2}{n_2}}$$

Our expectation that ask order prices will remain high means that we should see more significant positive results for the weighted than for the unweighted ask data.

RESULTS

Summary Statistics

Figure 2 is a graph of the path of the average price bubble considered in our study. To create the graph, for each stock, we calculate each day's price relative to the peak price during its bubble and center each series on its peak, day zero. Our sample includes bubbles of different duration, ranging from three months to six years. The x axis of the graph allows for the longest interval, from three years before day zero to three years after, and each stock's data are included for its relevant interval. That is, all of the stocks are included in the three-month interval, data for the three-month bubble duration stocks drop out of the graph for intervals greater than ± 42 days from day zero, and so on. The thin solid line on the graph shows the number of stocks for which there is data on a given day relative to day zero. The price-to-peak-price ratios are averaged for each day and graphed as the bold line. The upper and lower dotted lines represent the 95th and 5th confidence intervals, respectively, for the average ratio.

The bubble is quite symmetric, much more symmetric than those depicted in the discussions of laboratory bubbles. Surprisingly, the area under the inflating curve is slightly smaller than that of the deflating curve, suggesting that prices rise faster than they fall. In experimental markets, the opposite is true. Experimental bubbles typically grow over most

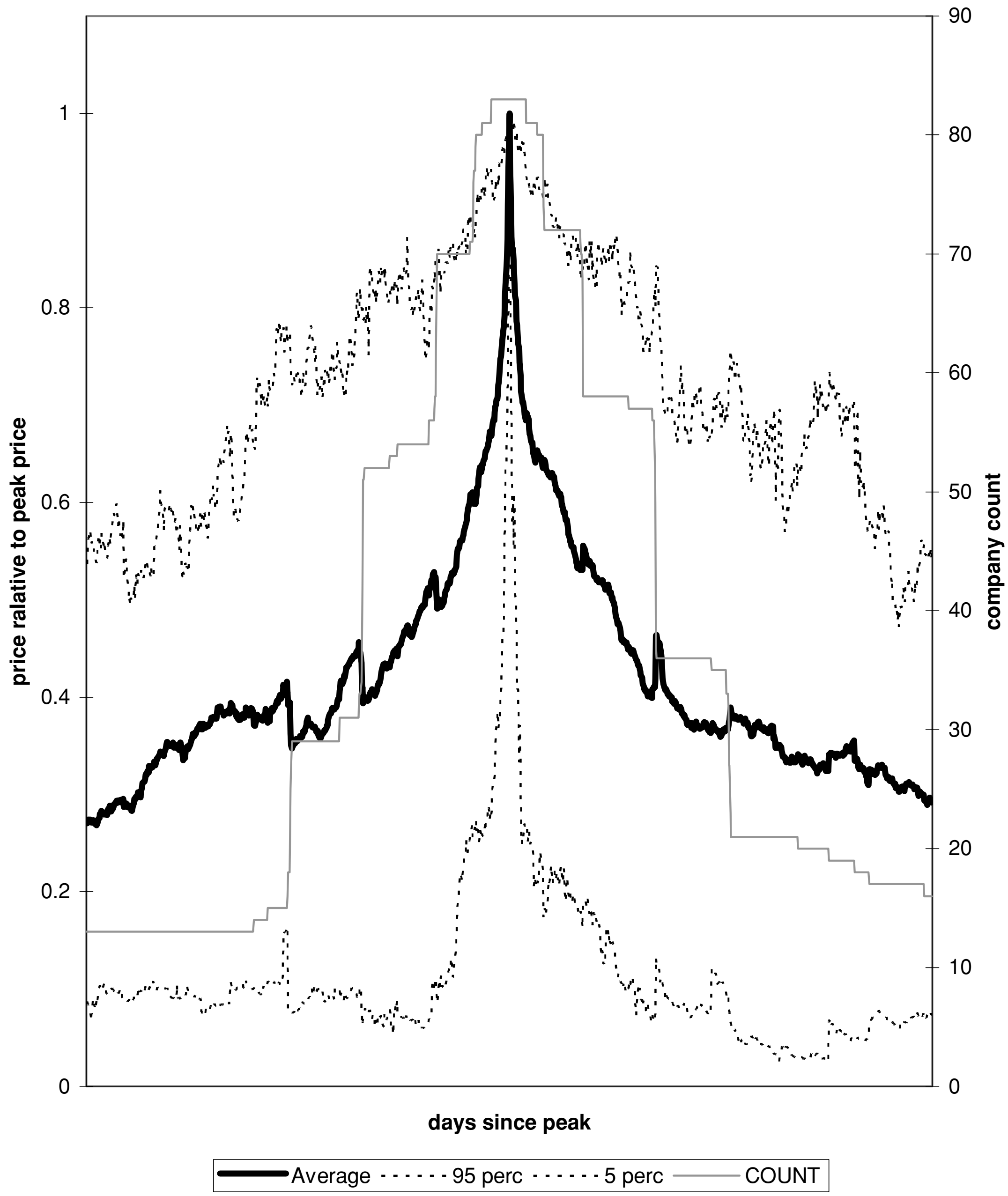


FIGURE 2 Average price ration relative to peak, with number of companies.

trading intervals and crash only near the end of the experiment. As we discuss in the context of volume, we surmise that the limit order structure and the lack of an end date account for the difference between the two market types. The distinctive steps in the count (thin solid) line, an artifact of our interval selection process, align with the large disruptions in the average price ratio line, suggesting that those disruptions are a result of adding blocks of data, rather than a feature of the price ratio.

Statistics in Table 1 summarize the raw data as well as the weighted and unweighted total volume variables. The average ask volume is larger than the average bid volume, consistent with the urgent desire to sell that accompanies a deflating bubble. In contrast, Aitken, Brown and Walter [1995] find greater bid volume than ask for the ASX as a whole, further indicating that bubble stocks exhibit different characteristics from general ones. Our weighting factor reduces the impact of stale orders on the volume. The average ask volume is deflated by 8%, compared with 7% deflation of the average bid volume, suggesting that prices alter so quickly that sellers' expectations lag changes in the market price. The average return is very slightly positive but not statistically significantly different from zero.

TABLE 1
Summary statistics; cross sectional over entire sample of stocks.

Variable	Number of observations	Mean	Standard error
Price	52087	\$5.85	8.358
Spread	50039	\$0.07	0.140
Return	52004	0.001	0.066
Price change	52004	0.000	0.331
Total bid volume (000s)	52088	340.939	1125.955
Weighted bid volume (000s)	52088	316.989	1048.274
Total ask volume (000s)	52088	466.026	1606.986
Weighted ask volume (000s)	52088	429.178	1450.121
Total bid volume minus total ask volume (000s)	52005	−125.575	1128.218
Weighted bid volume minus weighted ask volume (000s)	52005	−112.633	1010.509

Models

Two major objectives of this paper are 1) to show that the results established in experimental laboratory markets are relevant to field markets and 2) to show that our modifications increase the power of the original model. In Table 2 we summarize the results of testing the variations of the model on the bubble data.

Our results for field data are consistent with findings in laboratory markets. The laboratory model, our Equation (1), shows a significant correlation between price changes and lagged bid and offer volume (quantity) imbalance for about 55% (40%) of the potential field bubbles. Theory argues that the coefficient of the excess demand variable should be positive. Our results for Equation (1) show nominally negative coefficients for only about 7% of the sample, and all of those negative coefficients are insignificantly different from zero, with an average p value of 0.7168.

Our innovations improve the results markedly. Using returns increases the number of significant regressions by about 20%. Adding the weighting factor increases the number of significant regressions a further 2%. For the weighted, percentage version of the model, Equation (9), the correlation is significant for 77% of the field bubbles. Only 6% of the coefficients are nominally negative and again all of those are statistically insignificant.

Figure 3 explores the results of the Equation (10) regressions in more detail, graphing the p value of estimates of the coefficients of the excess demand variables against the number of observations in the regression. The lack of pattern argues against any spurious correlation between significance and number of observations.

TABLE 2
Summary table for significance of univariate regressions. This table summarizes the results of sets of univariate regressions. The column headings refer to the equations as discussed in the text. Equations (1) and (9) are tested with both number of orders placed (*Quantity*) and total volume of the orders (*Volume*). The first three rows of data refer to the statistical significance of the coefficient of the independent variable for the regression specified in the column heading (or, alternatively, to the statistical significance of the F test for the regression specified in the column heading). The integers in the cells of the first four rows of data are the number of stocks (out of 83) for which the equation (column heading) is significant in the range specified by the row.

$$p_{i,t} - p_{i,t-1} = \alpha_i + \beta_i(x) + \varepsilon_{i,t},$$

$$x \in \{(B_{i,t-1} - O_{i,t-1}), (Bvol_{i,t-1} - Ovol_{i,t-1})\}, \forall i \tag{12}$$

$$p_{i,t} - p_{i,t-1} = \alpha_i + \beta_i(wtBvol_{i,t-1} - wtOvol_{i,t-1}) + \varepsilon_{i,t}, \forall i \tag{4}$$

$$ret_{i,t} = \alpha_i + \beta_i(x) + \varepsilon_{i,t}$$

$$x \in \{relBMA_{i,t-1}, relBMAvol_{i,t-1}\}, \forall i \tag{9}$$

$$ret_{i,t} = \alpha_i + \beta_i(relwtBMAvol_{i,t-1}) + \varepsilon_{i,t}, \forall i \tag{10}$$

	Equation (1)			Equation (9)		
Level of significance /Order	*Quantity*	*Volume*	Equation (4)	*Quantity*	*Volume*	Equation (10)
1%	21	27	28	45	52	51
1%<X<5%	8	10	13	11	7	9
5%<X<10%	4	9	7	3	4	4
Total significant at 10% or better out of 83	33	46	48	59	63	64
Percent significant	0.3976	0.5542	0.5783	0.7108	0.7590	0.7711
Number of negative coefficients	6	6	7	7	3	5
Average p value of negative coefficients	0.7168	0.7168	0.6815	0.6815	0.8700	0.8706

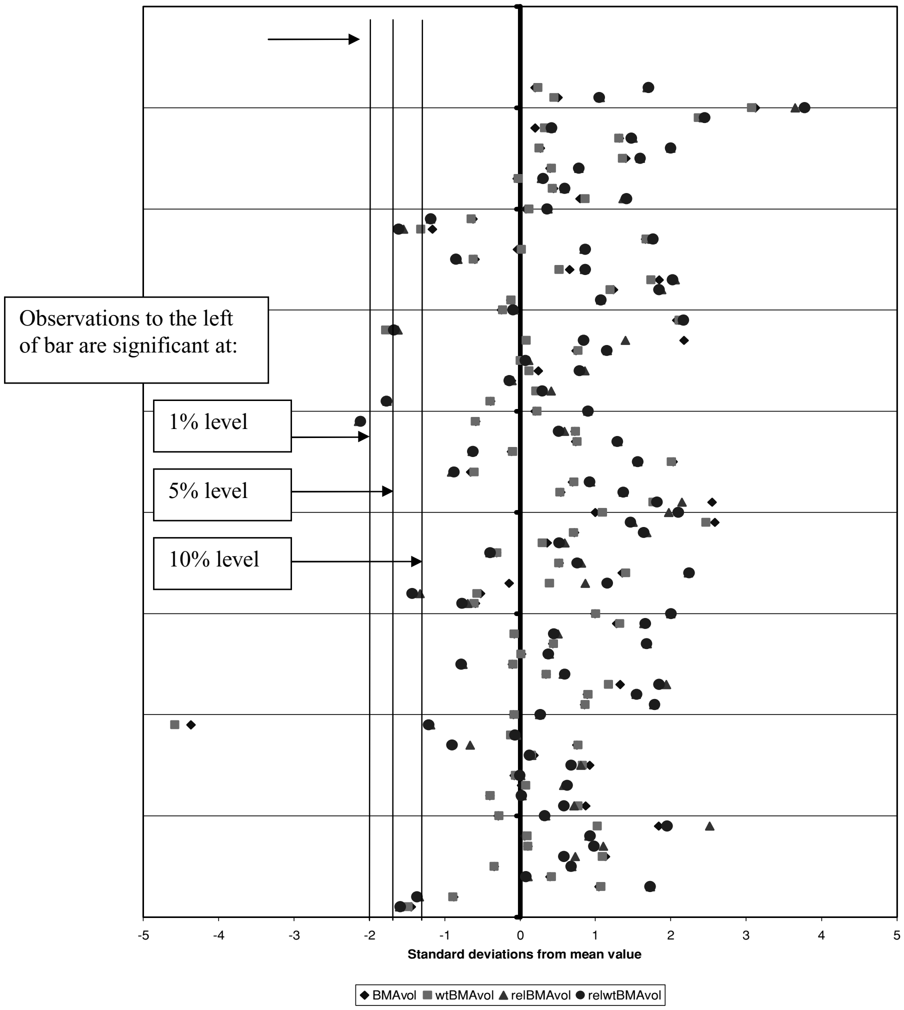


FIGURE 3 Excess demand on peak day relative to average pre-peak excess demand; Significance of excess demand coefficients, equation (10)

Volume

Another element of experimental bubbles is differential volume for pre- and post-peak periods. In experimental markets, where the termination point of the risky asset is known, bubbles collapse abruptly and on reduced volume. Figure 2 showed that field market bubbles collapse more slowly. Table 3, Panel A considers the differential in order volume before and after the peak price is achieved; Panel B shows the differential for transaction volume. For order volume the results are inconclusive. We hypothesized that bid volume after the peak would be lower than before the peak. Although the bid means are significantly different from each other for 84% of the stocks in the sample, pre-peak volume is significantly greater than post-peak for only 58% of the stocks in the sample. For 37% of the sample, pre-peak volume is less than post-peak (90% of those are statistically significant). The weighting factor slightly reduces the number of cases in which pre-peak volume is significantly greater than post-peak. The effect of the weighting factor could be interpreted as weak evidence that buy-side investors expect prices to fall more dramatically than they do.

In experimental markets, post-peak ask volume is lower than pre-peak. With our field data, we find that although pre-peak ask volumes are different from post-peak for 81% of the stocks in the sample, pre-peak volume is significantly greater than post-peak for only 29% of the sample. The weighting factor decreases the number of cases where post-peak ask volume is greater than pre-peak and increases the number of cases where pre-peak ask volume is significantly greater than post-peak. We interpret these statistics to mean that sell-side investors underestimate the speed of decline in prices as the bubble crashes. This evidence supports our hypothesis that investors who hold a bubble stock whose price has crashed perceive that the price will eventually rebound.

CONCLUSION

In this paper, we link experimental finance results and empirical or field data. We find that many of the observations

TABLE 3
Difference of pre- and post-peak mean volumes. This table shows summarized results of the difference in means test (Equation 11) applied to the volume of orders (Panel A) or transactions (Panel B) before and after the date when the peak price is achieved for each of the stocks in the bubble sample. Panel A reports results for the total bid and total ask volumes and for the weighted bid and weighted ask volumes, weighted by the factors calculated with Equations (2) & (3), respectively. The first section of Panel A shows the number of stocks for which pre-peak order volume is greater than post-peak. The second section of Panel A shows the number of stocks for which pre- and post-peak volumes are significantly different from one another. The final section of Panel A shows the number of cases for which post-peak volume is greater than pre-peak, and the levels of significance.

Panel A: Order volume for bubble stocks							
Pre-peak volume > post-peak	1%	1%<X <5%	5%<X <10%	Total significant/83	Percent significant		
	Level of significance of test statistic, one-tailed test						
Bid	44	0	4	48	0.5783		
Wted bid	44	0	1	45	0.5422		
Ask	22	2	0	24	0.2892		
Wted ask	24	2	0	26	0.3133		
	Level of significance of test statistic, two-tailed test						
Pre-peak volume ≠ post-peak	1%	1%<X<5%	5%<X<10%	Total significant/83	Percent significant		
Bid	65	4	1	70	0.8434		
Wted bid	62	7	70	0.8434			
Ask	0.8072						
Wted ask	58	7	2	0.8072			
	Level of significance of negative test statistic, one tailed test						
Pre-peak volume < post-peak	Number of cases	Percent of total	1%	1%<X <5%	5%<X <10%	Sig/Nobs #	% NVS*
Bid	31	0.3735	26	1	1	28	0.9032
Wted bid	31	0.3735	26	1	1	28	0.9032
Ask	54	0.6506	42	2	3	47	0.8704
Wted ask	50	0.6024	42	0	4	46	0.9200

Panel B: Transaction volume for bubble stocks					
	Level of significance of test statistic				
Pre-peak volume > post-peak	1%	1%<X<5%	5%<X<10%	Total significant/ 82	Percent significant
Pre-peak volume > post-peak (one- tailed test)	22	3	6	31	0.3780
Pre-peak volume ≠ post-peak (two- tailed test)	43	4	4	51	0.6220
Pre-peak volume < post-peak (one- tailed test)	25	1	2	28	0.3415

Note: #total significant/number of cases; *percentage of negative values that are significant

from the laboratory markets can be applied to field markets. Moreover, we propose modifications to the original model so that it better reflects field market conditions. Our modifications, including using volume rather than number of orders, weighting orders by their proximity to the best order, considering relative rather than absolute changes, and considering additional tests to account for the extra variability of field markets, improve the performance of the laboratory model. The original laboratory model exhibits significant results for 40% of the stocks; our modifications increase percentage of significant regressions to 77%.

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NOTES

1. For example, Blume, MacKinlay, and Terker [(1989)] use order imbalance, measured as dollar volume transacted at the ask minus dollar volume transacted at the bid, in discussing the market crash of October 19, 1987. Brown, Walsh and Yuen [1997] consider Granger causality between log price returns and order imbalance measured as number (dollar value) of ask orders divided by number (value) of ask plus bid orders. Verhoeven, Ching and Ng [2004] use a volume of shares at the best five ask prices divided by the sum of the volume of shares at the best five ask and the volume of shares at the best five bid prices as their order imbalance variable.
2. Brunnermeier and Nagel [2004] comment on the problem of companies with negative earnings, stating that “Based on price-to-earnings

ratios, it is then hard to distinguish an overpriced internet company from, say, a distressed 'old economy' manufacturing company" (p. 2017). Their solution is to rank companies by their price/sales ratios, sort them into quintiles and form portfolios. This technique is also context bound, however, a situation we sought to avoid.

3. These are not, however, micro-cap stocks. A few of the smallest companies included in the S&P/ASX200 benchmark index have market capitalizations of around A$1 billion.
4. More information about the companies in the study is available from the authors.
5. 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
6. See Gerety and Mulherin [1992].
7. Specifically, the ASX states that "An order may be purged because: 1) It has expired. 2) The order price is too far away from the current market (see next endnote). 3) The security will trade on an 'ex' basis of quotation from the following day. 4) The security has been suspended or delisted. 5) The security has been reconstructed." Source: www.asx.com.au
8. 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, all in Australian dollars: 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. Source: www.asx.com.au.
9. *BMA* signifies 'bid minus ask.'
10. Since we define our bubble period as equal intervals before and after the peak price date, this procedure divides the sample (almost) in half.

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