The dynamics of trader motivations in asset bubbles

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Abstract

Asset market experiments are analyzed by distinguishing, *ex post facto*, participants who trade on fundamentals versus those who trade on momentum (i.e., buying when price is rising). The distinction is made when prices are above fundamental value, so that (in each period) those who have more offers than bids (net offerers) are classified as fundamentalists while those who have more bids than offers (net bidders) are defined to be momentum players. By analyzing the data of individual behavior we are able to address a number of key questions regarding bubbles. We find evidence that the cash supply of the momentum traders diminishes and the cash supply of the fundamental traders increases as the bubble forms. This suggests that the bubble is fueled by the cash of the momentum players and the reversal is caused by inadequate cash in their possession. These data are used in conjunction with a difference equation for price dynamics for two groups. The momentum traders exhibit a positive coefficient for price derivatives and a very small negative coefficient for trading based upon the deviation from fundamental value. Surprisingly, however, the fundamental traders, who exhibit a positive coefficient for trading on valuation, also exhibit a significantly positive coefficient for trend based buying. Thus, even those who are net offerers, classified as fundamentalists, are selling less and buying more of overvalued stock when there is a strong positive recent price change. There is also evidence that some fundamentalists change strategy to momentum trading as prices soar. An additional result is that the trend coefficient of the momentum traders vanishes with the implementation of an "open book" that allows traders to see all trades as they are entered.

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1. Introduction

Financial bubbles such as the one high-tech/internet bubble of the late 1990's have posed a significant challenge to the efficient market hypothesis (EMH). At the later stages of this bubble, stock prices were so far removed from valuation that they appeared to be completely disjoint from the classical expected return models. Yet there have been only modest efforts in the academic community to understand the mechanisms that underlie this tremendous deviation from realistic value—even though a large segment of the population lost trillions of dollars as a consequence. Several years after this bubble we have little more knowledge about the strategies and motivations of individuals than we did at the time. Of course, this bubble is only the latest of many such episodes that

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include the 1980's bubble of Japanese stocks, the 1920's in US stocks, as well as historical bubbles of previous centuries. The 1990's bubble presented perhaps the biggest surprise in that it occurred at a time when information was so readily available from a variety of sources, thereby eliminating a key hypothesis that incomplete information alone is to blame.

Market bubbles have been studied extensively from one perspective, namely, experimental economics (see Davis and Holt [1993] for a review). Since the 1980's researchers have produced hundreds of bubbles in asset market experiments in which traders can buy or sell an asset through a computer network (see e.g., Sunder [1995], Sonnemans et. al. [2004], Hommes et. al. [2005]). At first, experimenters sought to find conditions under which a bubble could be created. Surprisingly, bubbles arose without any specific mechanisms to create them. As in the world markets the initial bubbles results were met with denial, with critics claiming that a number of elements missing in these experiments could account for the large deviations from fundamentals. These included the absence of short selling, margin buying, a futures market, etc. However, experiments showed that bubbles persisted when any of these were introduced (Porter and Smith [1994]). Only experience as a group tended to reduce the size of the bubble (Smith, Suchanek and Williams [1988]). Of course, in world markets there are always some newcomers with little or no experience, so this discovery is only limited consolation for EMH. One approach that has provided an explanation for the motivations that underlie bubbles was presented in mathematical models that incorporated a preference function that depended not only on deviation from fundamental value but on the price trend as well (see e.g., Caginalp and Ermentrout [1990], Caginalp and Balenovich [1999] and references therein). These models incorporated the conservation of cash and asset, and made the predictions that (i) a larger cash supply would result in a larger bubble; (ii) a lower initial price would yield a larger bubble, both contrary to the expectations of EMH. Both of these predictions were confirmed by experiment (Caginalp, Porter and Smith [2001]). These experiments also demonstrated a role, though limited, for the open book, whereby all traders can see the full set of orders, in mitigating the size of the bubble.

There are two main advantages in using experiments: (i) conditions can be adjusted and experiments repeated; (ii) detailed data sets about the actions of particular traders are available. In this work, we utilize the latter feature, as we distinguish the behaviors of different traders and test hypotheses with this information. The first step is to define a criterion for separating traders who trade on fundamentals from those who trade on momentum. Some traders who do not fit either criterion are in a third group. We can then test a basic hypothesis that the peak of the bubble occurs when the momentum traders have depleted much of their cash. This hypothesis is confirmed. With the price being far above the actual value at this point, the fundamentalists are not interested in buying, and consequently the trading price drops precipitously.

Beyond this result we seek to utilize a discretized version of the differential equations discussed above to evaluate the coefficients related to each of the two groups. In particular, we use the data in terms of cash and asset supply for each trader and the trading prices to see if the coefficients are of the correct sign and statistically significant. If so, it provides a confirmation of the model using two distinct groups. Furthermore, we would like to determine whether the momentum traders are influenced by fundamentals, and vice versa. Also of interest is whether the presence of an open book tends to diminish momentum trading.

2. The experiments

We utilize the data from experiments reported by Caginalp et al. [2003]. These experiments consisted of 9 to 14 participants trading through a computer network in which there are 15 periods of three minutes each with a one minute break after each period. A very detailed set of interactive instructions on the computer terminal requires each participant to enter, cancel and understand trades. The instructions are self-paced, as the program does not allow the participant to move on until each step is carried out correctly. The instruction part of the session lasts approximately one hour. Thus, the format of the instructions eliminate the possibility that a participant reads the instructions, but is confused about the "nature of the task" or the "structure of the asset." Such confusion has been observed as a source of bubble formation in experiments of Lei, Noussair and Plott [2001], and Lei and Vesely [2004]. There is also a practice session at the end of the instructions, so that cognitive errors are minimized in subsequent trading. Participants are informed prior to the start of the experiment that each share of the asset pays a dividend with expectation value 24 cents at the end of each period. Hence the fundamental value -- which is computed for the traders at the end of each period as the sum of dividends expected to be obtained until the end of the experiment—is a declining function that starts at \$3.60 and is 24 cents during the 15th period. The value of the asset (namely 24 cents times the number of periods remaining) is computed and remains on the computer screen and is updated at the start of each period. Hence this eliminates the possibility that traders are making decision errors due to miscalculations, thereby further reducing the role of "confusion" in bubble formation. The double auction mechanism yields a single price for each period. In other words, each participant can place orders to buy or sell any quantity of shares. In a typical experiment, prices start lower than \$3.60 but start rising during the first few periods, moving past the expected dividend value until a peak is reached somewhere between the eighth and 14th periods. Prices plummet shortly after this peak. Fig. 1 presents a typical bubble experiment.

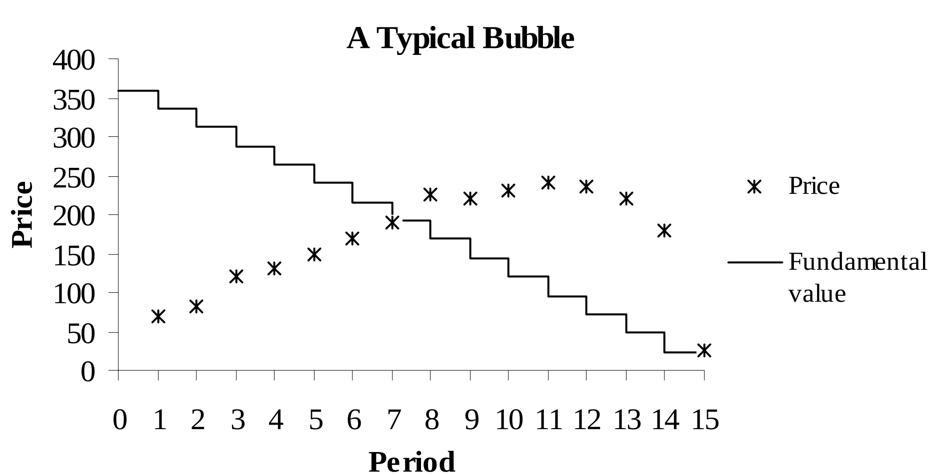

Fig. 1. A typical bubble experiment.

2.1 Trading mechanism

To implement the trading, the experiments utilize an order-driven market mechanism, whereby participants can submit limit orders to buy or to sell from both sides of the market. Simultaneous execution of submitted limit orders at a single moment in time at a single price is the essence of this trading mechanism. Two slightly different variations of this basic trading mechanism are used in the experiments. The first mechanism, used in 12 "closed book" experiments, is a sealed bid double auction in which the subjects can submit limit orders but cannot see the orders of the other participants. They can only see the resulting price and volume. The second trading mechanism is a standard call auction in which participants enter their respective bids or asks and see them entered into the auction in real-time. If, based upon competing bids or asks, the subjects wish to alter their price or number of shares, they can do so. In these 11 "open book" experiments, participants see all submitted orders, but not the identity of the traders placing the orders. The clearing price in both trading mechanisms can be regarded as a consensus price as its determination is based on the full set of submitted bids and asks. The uniform execution price is determined at the end of the period by ordering the bids and asks in descending and ascending order respectively, and matching the quantity supplied to the quantity demanded. Transactions occur when the bid and ask prices are equal. Traders who bid above the clearing price become buyers and traders who submit asks below the clearing price become sellers.

2.2 Classifying trader behavior

Using the experimental data, the classification of each trader into one of the three groups is done in each period. We do not make the assumption that a trader of one type will necessarily remain so for the entire experiment. A trader can be classified in a different category in different periods. The data will determine the extent to which traders change strategies. Momentum traders buy stocks with the expectation of a continued rise in prices and sell stocks with the expectation of a continued fall in prices. Fundamental traders trade shares based on the expected fundamental value of the asset. They sell when they believe that an asset is overvalued and buy when they believe an asset is undervalued. We do not claim to classify behavior as rational or irrational. We distinguish between momentum and fundamental trading. Indeed, there may be rational reasons for an investor to be a momentum trader (see DeLong et. al. [1990]).

On the basis of the definitions above, we separate the traders in each period in which the clearing price is higher than the fundamental value into three groups: fundamental traders, momentum traders and neutral traders. To classify each trader into one of the three groups we assign a positive point for each fundamental bid or ask and a negative point for each momentum bid or ask that the trader submits. Classifying a trade as "fundamental" requires a bid to buy at a price below the expected dividend value or an ask to sell at a price that is above this value. Similarly, a "momentum" bid is one that offers to buy at a price above the expected dividend value or an ask to sell at a price that is below this value. In order to be able to distinguish between the two, we focus on periods in which the price exceeds the fundamental value. If the sum of the points that a trader accumulates throughout the period is equal to or greater than one, we classify this trader as a fundamental trader. If the sum is less than or equal to negative one, the trader is assigned to the group of momentum traders. All traders who accumulate zero points throughout the period comprise the neutral group.

3. Experimental results

To answer the questions posed above we test first whether the levels of cash in the hands of the momentum and fundamental traders differ significantly through time. In an earlier paper Caginalp, Porter and Smith [2001] show that the level of cash in an experimental economy is highly correlated with the size of a bubble for both the open-book and closed-book experiments. Taking this one step further we suggest that it is the bidding of the momentum traders that fuels the bubble. Therefore, we hypothesize that towards the peak of the bubble the cash holdings of momentum traders decrease while those of fundamental traders increase.

To compare the levels of cash of the momentum and fundamental traders we combine the data from all closed and open book experiments and compare the levels of cash of each group of traders from each period starting with five periods before the peak price formed in the market, and ending with two periods after with a *t*-test, assuming that the two samples have unequal variances.

Table 1 reports the amount of cash of each group from period *T*-5 to period *T*+2, with *T* denoting the period in which the price is the highest. The data include all eleven open-book and twelve closed-book experiments. The t-tests confirm that at the group level the fundamental traders have significantly more cash (at least at the 10% level of significance) than the momentum traders in each period from period *T-5* to period *T+2*.

	Average cash of fundamental group	**Average cash of momentum group**	**Average cash of neutral group**
T-5	8892.39	3722.89	2858.50
T-4	7464.50	4903.79	2635.14
T-3	6855.69	4481.00	3995.31
T-2	7786.74	4450.44	4078.59
T-1	8866.09	4042.93	3083.71
T	9640.20	3049.87	3753.41
T+1	9385.28	3104.33	3847.60
T+2	10402.20	2457.93	3543.07

Table 1. Average cash holdings across groups.

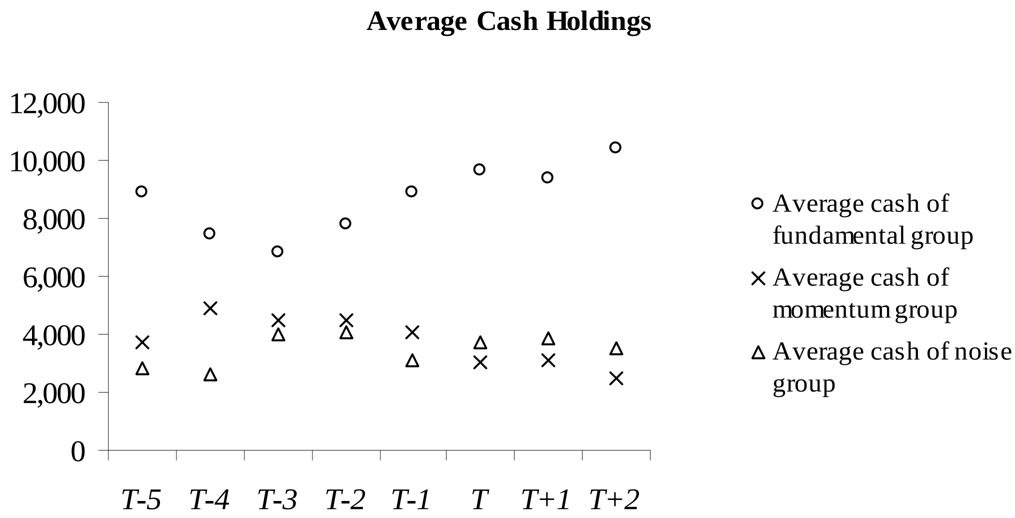

Fig. 2. Average cash holdings across groups.

Figure 2 shows that the cash holding of the fundamental group increases from T-3 to T+2. Similarly, the cash holding of the momentum group generally decreases during T-4 to T+2. The earliest periods in that graph correspond to the periods in which the bubble is not yet very large so that the distinctions in trader behavior are not as pronounced. The statistical significance of these changes will be evident below with additional tests. This suggests that the fundamentalists are lightening up on shares as the price moves further away from the expected dividend value. Similarly, the momentum traders put an even greater share of their cash into stocks as the price moves higher.

To obtain more detailed information on the characteristics of individual traders in the experiments, we also investigate the levels of cash on a per trader basis. Table 2 reports the cash levels from period *T*-5 to period *T*+2 on a per trader basis. The *t*-test results indicate that the average momentum trader has significantly less cash than the average fundamental trader in each of the time periods.

	Average cash per fundamental trader	**Average cash per momentum trader**	**Average cash per neutral trader**
T-5	1674.52	1249.23	963.79
T-4	1623.20	1165.63	1210.24
T-3	1357.17	1241.25	1494.63
T-2	1522.75	1224.90	1457.01
T-1	1684.45	1051.09	1273.23
T	1656.37	1270.46	1234.94
T+1	1536.85	1275.74	1332.85
T+2	1502.63	1044.94	1308.47

Table 2. Average cash holdings per trader across groups.

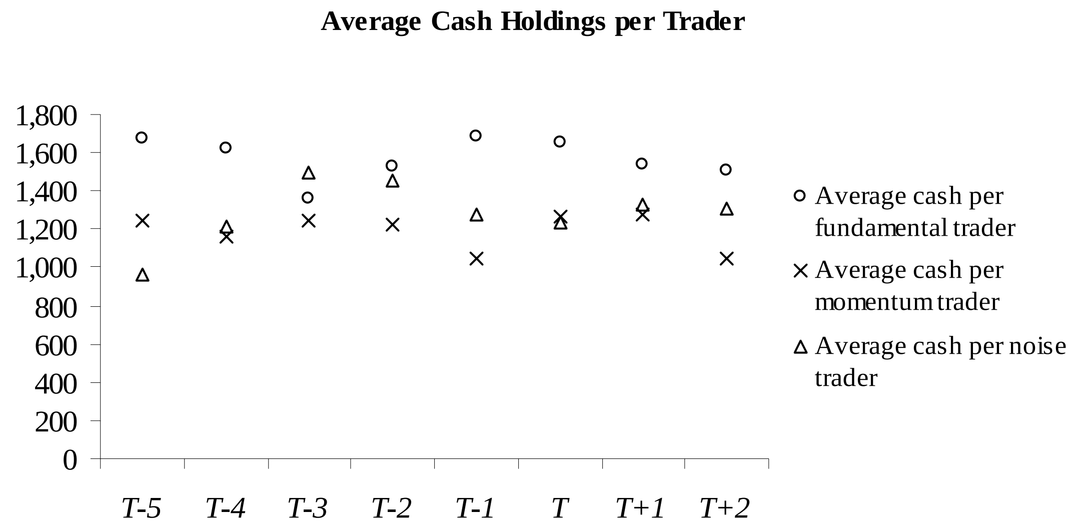

Fig. 3. Average cash holdings per trader across groups.

The average cash per trader data is not as pronounced as the total amount of cash for each group, since part of the equation involves the number of traders of each type. We will see below that the average number of momentum traders decreases from 4.14 in period *T*-4 to just 2.26 in period *T*.

The difference in the levels of cash (and asset) are likely to be very important in terms of timing the peak. Once the momentum traders are below some critical level of cash there is very little to power further rises, since the fundamentalists are unlikely to buy, and the remaining group (neutral traders) are unlikely as a group to provide a significant net buy/sell that would fuel the rally.

To better investigate the evolution of the cash positions of the two types of traders through time we calculate the correlations of time with cash presented in Table 3. All correlations are significant.

	Average cash of fundamental group	Average cash of momentum group	Average cash per fundamental trader	Average cash per momentum trader
T-5* to *T	0.45	-0.49	0.11	-0.17

Table 3. Correlations of cash with time.

Table 3 shows that the amount of cash of the fundamental group and the amount of cash of the average fundamental trader generally increase through time, while the amount of cash of the momentum group and the amount of cash of the average momentum trader generally decrease through time.

Further Table 4 reports the correlations between the variables using the observations from all peak periods from all experiments. The results reveal that the total cash in the hands of the fundamental traders has a negative effect on the maximum positive deviation of price from fundamental value at the peak consistent with our hypothesis. The greater the amount of cash of the fundamentalists is, the smaller the bubble is. The correlations also show that the higher the cash of momentum traders is, the higher the difference of price from fundamental value, or the larger the bubble is.

	Price – fundamental value	Average cash of fundamental traders	Average cash of momentum traders	Average cash per fundamental trader	Average cash per momentum trader
Price – fundamental value	1	-0.12	0.46	0.18	0.19
Average cash of fundamental traders	-0.12	1	-0.29	0.66	0.08
Average cash of momentum traders	0.46	-0.29	1	0.20	0.57
Average cash per fundamental trader	0.18	0.66	0.20	1	0.25
Average cash per momentum trader	0.19	0.08	0.57	0.25	1

Table 4. Correlations at the peak.

As expected there is a negative correlation between the levels of cash of the momentum and the fundamental groups at the peak. The higher the proportion of cash held by the fundamental group, the lower the cash level of the momentum group is. Also there is a positive correlation between the levels of cash of the average momentum trader and average fundamental trader. The higher the total cash endowment in an experiment is, the higher the cash per traders is. A *t*-test of the difference in the number of traders of each type when the deviation from fundamental value is the highest shows that the number of fundamental traders is significantly greater than the number of momentum traders. On average there are twice as many fundamental traders as momentum traders at the peak of the bubble.

	Average number of fundamental traders	Average number of momentum traders	*p*-value
T-5	5.56	3.11	0.04
T-4	4.79	4.14	0.51
T-3	4.94	3.50	0.12
T-2	4.88	3.47	0.04
T-1	5.45	3.41	<0.01
T	5.70	2.26	<0.01
T+1	6.15	2.30	<0.01
T+2	6.93	1.73	<0.01

Table 5. Average number of traders comparisons.

4. Price formation

This section examines the effect of momentum and fundamental traders on the determination of prices in the experiments. We use an excess demand model whose basic equilibration principle is based on the premise that prices move in the direction determined by supply and demand in the market. The model, presented below, generalizes those introduced by Caginalp and Ermentrout [1990] (see Caginalp and Balenovich [1999] for other references). It assumes that both the fundamental and momentum traders take into consideration past price changes and price deviations from fundamental value. Other works, particularly in recent years have also focused on similar ideas, including Lux [1995], [1998], Brock and Hommes [1998], Lux and Marchesi [2000], Farmer and Joshi [2002] and Westerhoff [2004].

The market prices evolve according to the forces of demand and supply

$$\frac{\tau_0}{P}\frac{dP}{dt} = \frac{D}{S} - 1, \tag{1}$$

where D and S denote the demand and supply at time t. The model indicates that prices move in the direction of clearing the market.

The demand for shares is a function of the cash in the economy and a preference for holding a portion of wealth in stocks. The supply of shares is a function of their price, quantity and a preference rate of converting stocks into cash. If N_0, j, k^j, M^j, N^j denote the number of different types of traders, the trader type, the conversion preference rate of cash into stocks of traders of group j, the cash of group j, and the number of shares owned by group j, then $D = \sum_{j=1}^{N_0} k^j M^j$ and $S = \sum_{j=1}^{N_0} \left(1 - k^j\right) N^j P$. Hence (1) transforms into

$$\frac{\tau_0}{P}\frac{dP}{dt} = \frac{\sum_{j=1}^{N_0} k^j M^j}{\sum_{j=1}^{N_0} \left(1 - k^j\right) N^j P} - 1. \tag{2}$$

The conversion preference rate of cash into shares, k^j, is a function of two components: a momentum or a trend factor, $\frac{dP}{Pdt}$, and a valuation factor, $\frac{P_a - P}{P_a}$, where P_a denotes the fundamental value of a share. The first component represents the instantaneous rate of change in price relative to its current level, while the second component represents the deviation of the trading price from the fundamental value of a share. Thus

$$k^j = \frac{1}{2} + \frac{Q_1^j}{P}\frac{dP}{dt} + Q_2^j\left(1 - \frac{P}{P^a}\right), \tag{3}$$

where Q_1^j and Q_2^j are constants.

Thus, k^j can be regarded as the rate at which a unit of cash is submitted to the market, while 1-k^j is the rate at which a unit of asset is submitted for sale. Note that ½ represents the neutral preference rate, where the rate of submission of shares for cash equals the opposite preference. In principle, the rate k^j can depend on as many factors as there are reasons to buy or sell. Classically, the only motivation to buy would be the perception that the asset is undervalued. This component is quantified for group j through the coefficient Q_2^j. Our hypothesis is that momentum trading characterized by a preference for buying as the asset rises is also a motivating factor. The coefficient for group j is denoted Q_1^j. Note that the magnitude of Q_1^j will be decided by the data. If there were no momentum trading for any group we would have $Q_1^j = 0$ within statistical error.

With the assumption that only the fundamental and momentum traders exert influence on the price there are two groups of traders. Hence (2) reduces to

$$\frac{dP}{Pdt} = \frac{k^1 M^1 + k^2 M^2}{\left(1-k^1\right)N^1 P + \left(1-k^2\right)N^2 P} - 1 \qquad (4)$$

and (3) reduces to

$$k^1 = \frac{1}{2} + \frac{Q_1^1}{P}\frac{dP}{dt} + Q_2^1\left(1 - \frac{P}{P^a}\right) \text{ and } k^2 = \frac{1}{2} + \frac{Q_1^2}{P}\frac{dP}{dt} + Q_2^2\left(1 - \frac{P}{P^a}\right) \qquad (5)$$

Approximating $\frac{dP}{dt}$ with $P_{t+1} - P_t$ in (4), and with $P_t - P_{t-1}$ in (5) and substitution of (5) into (4) we obtain (6).

$$Q_1^1(P_{t+1} - P_t)\left(M_t^1 + N_t^1 P_{t+1}\right) + Q_2^1\left(1 - \frac{P_t}{P_t^a}\right)\left(M_t^1 P_t + N_t^1 P_t P_{t+1}\right) + Q_1^2\left(P_{t+1} - P_t\right)\left(M_t^2 + N_t^2 P_{t+1}\right) +$$

$$Q_2^2\left(1 - \frac{P_t}{P_t^a}\right)\left(M_t^2 P_t + N_t^2 P_t P_{t+1}\right) = \left(N_t^1 P_t P_{t+1} + N_t^2 P_t P_{t+1} - M_t^1 P_t - M_t^2 P_t\right)/2 \;, \qquad (6)$$

where *i* and *t* indicate the experiment and the period, respectively.

The basic strategy is to perform a multi-linear regression to estimate Q_1^1, Q_2^1, Q_1^2 and Q_2^2 (recall that the superscript refers to the group while the subscript is 1 for the trend and 2 for the valuation coefficient) using all of the data of the experiments. The cash and asset position of each trader can be computed. In some of the experiments the dividends were paid immediately after the period, adding to the cash position. This is taken into account in the difference equations. In performing this linear regression, however, we cannot assume that the data are all independent since many periods of data are generated by the same participants. A multi-linear regression can be done using the Fixed Effects Model that compensates for these dependencies, and is consequently more reliable than an ordinary linear regression. The results are presented in Table 6 and Table 7 for the closed and open book experiments, respectively.

Independent variable	Estimated coefficient	Estimated standard error	*t*-ratio	*p*-value
Q_1^1	0.447	0.239	1.866	0.07
Q_2^1	-0.037	0.005	-7.843	0.00
Q_1^2	0.509	0.152	3.349	0.00
Q_2^2	0.073	0.009	7.930	0.00

Table 6. Price dynamics for the closed book experiments.

Independent variable	Estimated coefficient	Estimated standard error	*t*-ratio	*p*-value
Q_1^1	-0.018	0.063	-0.290	0.77
Q_2^1	0.003	0.015	0.223	0.82
Q_1^2	0.101	0.048	2.100	0.04
Q_2^2	0.050	0.007	7.115	0.00

Table 7. Price dynamics for the open book experiments.

The R^2 is 0.82 for the closed book experiments and 0.71 for the open book experiments. The likelihood ratio test rejects the null hypothesis of joint non-significance at less than the 1% level of significance with χ^2_{15} of 135.4 and χ^2_{14} of 102.9 for the closed and open book experiments, respectively.

For the closed book experiments we find that the trend coefficient, Q_1^1, for the momentum traders is 0.447 with a standard error of .24 and p-value of 0.066. The value coefficient is significant with a p-value of 0 (to four decimal places). For the fundamental traders, the momentum coefficient, Q_1^2, is 0.51 with a standard error of 0.15 and p-value of 0.0013. The value coefficient, Q_2^2, is 0.073 with a standard error of 0.0092 and p-value of zero (to four decimal places). The complete statistics are displayed in Table 6.

Hence we see that the fundamental traders nevertheless are just as strongly influenced by price movements as the momentum group. In other words, if the recent price change in an overvalued stock is small, the fundamentalists are far more likely to sell than if the price change is strongly positive. Thus it appears that when prices initially move above fundamental value, there is generally a strong uptrend. The momentum traders are buying aggressively (as indicated by the coefficient Q_1^1). However, the fundamental traders are not selling aggressively, since their momentum coefficient Q_1^2 is also positive. Furthermore, since prices are not yet very far from fundamental value at this point, the entire term $Q_2^2\left(1-\frac{P}{P^a}\right)$ is not very large. Hence, prices rise further until (a) there is less cash in the hands of the momentum traders, and (b) the difference between the fundamental value and trading price is large enough to make the $Q_2^2\left(1-\frac{P}{P^a}\right)$ term more significant. This offers some insight into the initial puzzle in our data: there are more fundamental traders than momentum traders, yet the price encounters little resistance as it moves up past the fundamental value.

For the open book experiments we find that the trend coefficient of the momentum traders, Q_1^1 is within the standard error of zero, as is the value coefficient, Q_2^1. The fundamentalist group has a value coefficient Q_2^2 of 0.05 with standard error of 0.007 with a p-value of zero (to four decimal places). Hence we find that the fundamentalists exhibit a value coefficient that is similar to the closed book case. However, the trend coefficient is about one-fifth of the magnitude of the closed book experiments. Together with the zero trend coefficient for the momentum traders, this suggests that there is a clear difference in the trading strategies between participants in the two types of experiments. In the open book experiments, the traders who are net buyers above the fundamental value appear more like noise traders than trend based ones. In any case it appears that the open book framework has a strong dampening effect on trend chasing. It is known (Smith, Suchanek and Williams [1988]) that bids tend to dry up near the peak of a bubble. Perhaps in the open book case this becomes evident to participants who would be eager to buy when the price is rising sharply. With an open book they may become aware that the price has risen sharply but there are not many buyers left!

Previous papers (e.g., Caginalp and Ermentrout [1990]) have studied the mathematical properties of these equations in various parameter regimes. While large parameters for the momentum coefficient can result in unbounded oscillations, the parameters that we have estimated using this data result in a sufficiently small coefficient for the momentum coefficient so that the prevailing regime exhibits one stable equilibrium.

Other papers that estimate the impact of heterogeneous market participants using financial market data include Westerhoff and Reitz [2003] and Vigfusson [1997] using probabilistic methods.

6. Conclusion

Experimental asset markets contain much more data than just the trading prices. In this paper, we have utilized detailed data for individual traders. This has allowed us to classify the traders in terms of net bidders (momentum traders) or net offerers (fundamental traders) when the trading price is above the fundamental value. We find that the momentum traders have gradually diminishing cash (both as a group and per trader) and have cash levels near the lows when the bubble peaks. The opposite is true of the fundamental traders. This suggests that the bubble is fueled by the cash of the momentum traders, even though they are consistently outnumbered by the fundamentalists. The bubble seems to reverse due to the diminished buying power of the momentum players. The cash of fundamentalists increases as the peak is approached, but they are not interested in buying at this point. Thus one might summarize the buying at the peak as: “Those who would, could not; those who could, would not.”

The question arises as to how the price can move above the fundamental value so easily despite the fact that there are more fundamentalists than momentum traders. The price dynamics equations appear to provide an answer to this puzzle. Even those traders who are net sellers when the price exceeds fundamental value are strongly influenced by the trend, according to our statistical analysis of the difference equations. When the price is initially moving past the fundamental value, the premium is relatively small but the price derivative is often large. Thus, it seems that the fundamentalists are not selling very aggressively at this point. The statistics indicate that they are more likely to sell as the deviation from fundamental value increases and the price change is more muted. Hence, an asset whose price is considerably higher than fundamental value, and beginning to stall becomes very risky to own.

This analysis offers some insight into the high-tech bubble of the late 1990's, when a huge amount of cash poured into the market from recent investors who had little experience and were largely influenced by price movements. Part of the rationale for ignoring fundamentals was based on the idea that these benchmarks were antiquated metrics. As the market moved into the stratosphere in comparison with fundamentals, one might assume that more seasoned investors would be selling. If one were to extrapolate from the experimental analysis, one could conjecture that the fundamentalists during the high-tech bubble were also somewhat reluctant to sell as they observed sharply rising prices. As prices began to stall, however, one expects that the fundamentalists with stock are the first to sell. This may explain the fairly rapid turn in the market -- in the absence of much new and negative information -- in early 2000, when stocks which had been rising rapidly for some time stalled briefly before moving decisively lower. When prices are no longer rising, the value buyers could not be expected to step in until the prices were a tiny fraction of the peak trading price. Of course, once the trend is clearly downward, the momentum traders sell in force. Without any significant group with interest in buying, and many interested in selling, prices fall precipitously.

Our analysis displays the interaction between the strategies of different types of traders with their cash/asset position. Understanding this relationship is the key to the dynamics of financial markets. Contrary to the efficient market idealization, there are different motivations behind trades, and it would be impossible to predict where these motivations would lead without having a quantitative basis for assessing the impact of these traders. In gauging the effect of a particular group the sentiment and strategy must be combined with their cash and asset positions within some set of price dynamics equations.

The equations we present do not have any *a priori* bias toward behavioral finance. If there were no significant tendency for traders to buy on rising prices, that particular coefficient would simply be estimated as zero by the statistical procedure. Hence this hybrid approach (statistical combined with difference equations) has the advantage of minimizing any bias in modeling.

As noted earlier, traders are classified during each period, and we now examine the transition rates between the momentum and fundamental groups during the periods T-4 to T+2. The details are presented in the Appendix. In general we find that the transition from momentum to fundamental is reasonably low (about 12%) through period T-2. Near the peak of the bubble, in periods T-1 through T+1 the transition probability triples to 36%. This is consistent with a simple learning process (i.e., participants are learning to focus on the realistic value) though it does not appear to be a linear function of time (see Appendix). When we examine the transition from fundamental to momentum, the same learning hypothesis would suggest <u>fewer</u> such transitions with increasing time. We find a more complex picture, however. Only 9% make the transition from fundamental to momentum during periods T-4 and T-3. Later, against a backdrop of soaring prices (and declining fundamental value), the transition probability jumps to 37% in period T-2, suggesting that traders are not simply learning to focus on valuation. Rather, even some of those who started with a sound valuation strategy (i.e., not bidding on the asset at prices that are clearly more than the expected return) are swept into momentum trading with rapidly rising prices. This is a further indication that the cause of the bubble is not simply inexperience and confusion with trading strategy. A key cause is the abandonment of value based investing by the value traders. After the bubble has peaked, the transition probabilities (fundamental to momentum) also decline.

In summary, the trading strategies of both groups appear to be very stable – under 11% in either direction during the early periods (T-4 and T-3) – *until* prices begin to rise rapidly above the fundamental value. It is only after a large rise in prices that a significant fraction of fundamentalists become momentum traders. Momentum traders change strategy in significant numbers only near the peak (T-1, T and T+1) as the soaring prices plateau. Thus, the traders appear to understand the trading strategy options available to them from the outset. Through adaptive learning they respond to the changing environment created by their fellow traders. For some, the value based investing appears to be a good strategy, but by period T-2 they observe that a momentum strategy would have served their interests better. Through adaptive learning they switch to a momentum strategy. Soon after this point, however, trading prices begin to level off since much of the available cash for buying so far above fundamental value has already been used. Once prices are no longer soaring, there is continued adaptive learning, particularly on the part of the momentum traders, as they switch in much larger numbers during T-1 and later periods to a value strategy. Thus there is a complex adaptive learning process that is intertwined with the basic conservation laws of cash and asset.

From the perspective of these experiments, a good forecaster of the peak is the sharp spike in the transition rate from fundamental to momentum strategies which occurs approximately two periods prior to the peak and about two or three periods after prices have moved above fundamental value. World market bubbles often exhibit a stage when long-time value investors relinquish their strategy and join the bubble.

With the insight gained from this analysis of experiments, the question arises as to how one can extract some of the relevant information in ordinary markets to utilize this approach. The necessary information consists of: (i) an estimate of the motivations of different groups, (ii) the asset sizes of the various groups. A key step in this direction would be to examine the data of the late stages of the high-tech bubble of the late 1990's and attempt to classify traders based upon the trade size, from 100 shares to block trades. One can then examine the nature of the trades, e.g., the fraction of these trades are on the "uptick," i.e., when the trade occurs on the high end of the spread, and the fraction of trades that occur when prices are rising within a specified small time period. If the information is available, one can determine whether the orders are limit orders or market orders. In previous studies, it has been shown that parameters estimated in experiments were close to those of the NYSE data for closed-end funds. Thus, the experimental parameters could be used as an approximation for the true values in the market, until optimization methods offer more accurate values. Surveys and brokerage data on the trading of individuals could also provide the useful information. Within our approach one needs only an average value for a group so that is possible to utilize aggregate cash/asset data for a group analogous to our experimental data.

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Appendix

The statistics are presented below for the transition rates between momentum and fundamental traders.

	Momentum trader to fundamental trader	**Fundamental trader to momentum trader**
***T*-4**	9.72%	11.00%
***T*-3**	10.71%	7.14%
***T*-2**	14.79%	37.16%
***T*-1**	37.41%	11.17%
T	27.81%	23.77%
***T*+1**	43.49%	22.62%
***T*+2**	29.70%	17.83%

Table 8. Average transition probabilities.

First we consider the conditional probability that a trader who is classified as momentum in one period will be classified as fundamental in the next period. Define a variable D as $D = 0$ for the periods T-4 through T-2, and $D = 1$ for periods T-1 through T+2. Then the linear regression for the transition probability on D leads to

$$\text{Momentum trader to fundamental trader transition probability} = 11.7 + 22.9\, D$$

so that there is strong statistical evidence (p-value = 0.004) that the transition probability triples during the peak of the bubble. The detailed statistics are displayed in Table 10. Figure 4 presents the results graphically.

Independent variable	Estimated coefficient	Estimated standard error	t-ratio	p-value
Constant	11.740	3.381	3.470	0.018
D	22.862	4.473	5.110	0.004
	R^2:83.9%	R^2Adj: 80.7%		

Table 10. Momentum trader to fundamental trader transition probability dynamics.

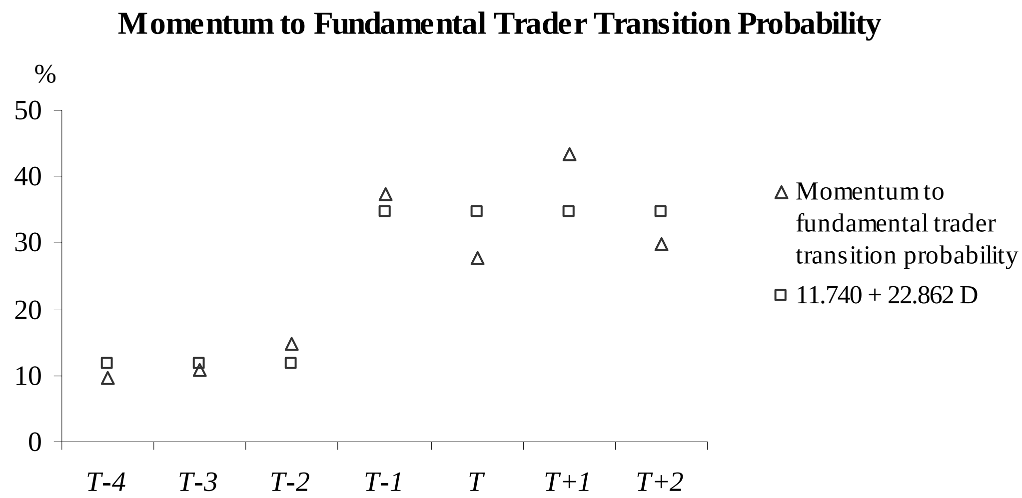

Fig. 4. Momentum to fundamental trader transition probability.

Next we consider the transition probabilities from fundamental to momentum trading. Now defining $D = 0$ for periods T-4 and T-3 and $D = 1$ for the remaining periods, we have the linear regression

$$\text{Fundamental trader to momentum trader transition probability} = 9.07 + 13.4\, D,$$

so that there is some statistical evidence (p-value = 0.12) that the transition probability increases by 50% during the peak of the bubble. The detailed statistics are displayed in Table 11. Figure 5 presents a graphical representation.

Independent variable	Estimated coefficient	Estimated standard error	t-ratio	p-value
Constant	9.070	6.117	1.480	0.198
D	13.440	7.238	1.860	0.122
	R^2:40.8%	$R^2 Adj$: 29.0%		

Table 11. Fundamental trader to momentum trader transition probability dynamics.

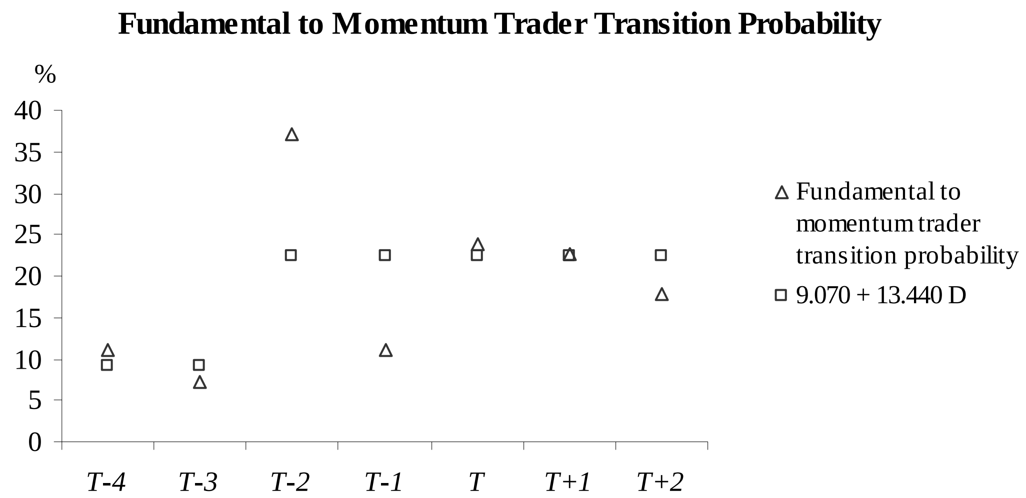

Fig. 5. Fundamental to momentum trader transition probability.

A quadratic regression for this transition probability yields the fitted graph in Figure 6.

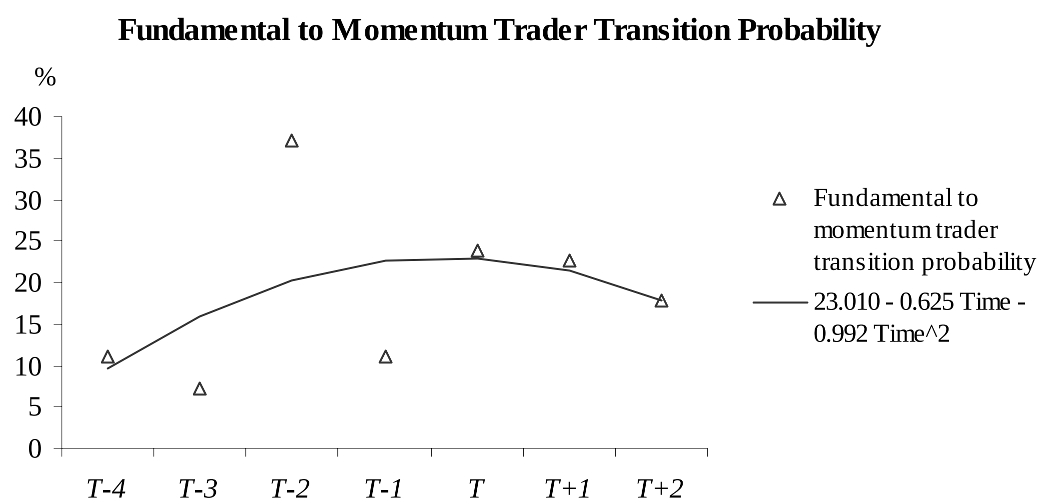

Fig. 6. Fundamental to momentum trader transition probability.

Hence the peak of the transition probability is near the peak of the bubble, and begins to fall off afterwards.

The regression equation is

$$\text{Fundamental trader to momentum trader transition probability} = 23.01 - 0.625\, Time - 0.992\, Time^2$$

Thus one observes an increase in the transition probability from fundamental to momentum as the bubble is forming, contrary to a basic learning model in which participants are initially confused about trading strategy but evolve uniformly toward a value oriented strategy. Similarly, Table 5 shows that the number of fundamental traders does not increase (and the number of momentum traders does not decrease) until the peak is attained. This is confirmed by regressing the numbers of traders in each group with time (through period T-1). During the period T-1 through T+2, however, a similar regression shows that there is a statistically significant increase in the number of fundamental traders (p-value = 0.028) and decrease in the number of momentum traders (p-value = 0.086). On average during these periods there is a net increase of 1 in the difference between the numbers of fundamental and momentum traders. Thus learning to trade on fundamentals begins only after prices fail to rise.

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